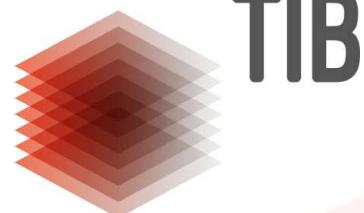


LEIBNIZ-INFORMATIONSZENTRUM  
TECHNIK UND NATURWISSENSCHAFTEN  
UNIVERSITÄTSBIBLIOTHEK



# NLPContributions: An Annotation Scheme for Machine Reading of Scholarly Contributions in Natural Language Processing Literature

Jennifer D'Souza and Sören Auer

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## What if ...

- The global scientific knowledge base would be more than a document repository
- Scientific information and knowledge would be FAIR also for machines
  - The FAIR data principles are a set of guiding principles in order to make scientific data findable, accessible, interoperable, and reusable in the current digital ecosystem ([Wilkinson et al. 2016](#))
- Currently
  - Findability could be better
  - Assuming OA, accessibility is OK
  - Interoperability and Reusability is non-existent
- The problem: The scholarly communications format is stuck in the last century
  - We have managed to digitize documents that used to be in print
  - While other areas have seen a transformative digitalization

# Our Objective

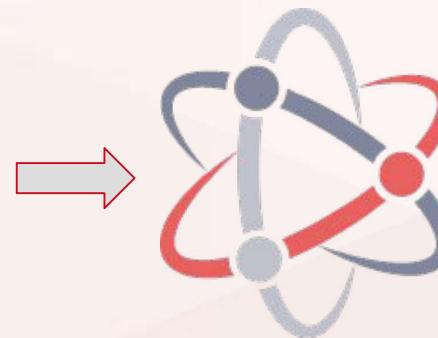
- To foster the *digitalization* of digitized scholarly articles

The image shows a digital workflow for scholarly research. On the left, a thumbnail of a research article from the European Heart Journal is displayed. The article title is "Iron-regulatory proteins secure iron availability in cardiomyocytes to prevent heart failure". The authors listed are Saba Haddad, Yong Wang, Bruno Galy, Mortimer Korf-Klingebiel, Valentin Hirsel, Abdul M. Baru, Fatemeh Restami, Marc R. Rohrbach, Jörg Heinlein, Ulrich Flügel, Stephanie Gross, Andre Renner, Karl Töischer, Fabian Zimmermann, Stefan Engel, Jens Jordan, Johann Bauersachs, Matthias W. Hentze, Kai C. Wollert, and Tibor Kemppainen. The journal is categorized under "BASIC SCIENCE". Below the article thumbnail, there is a small note: "© The Author(s) 2016. Published by Oxford University Press on behalf of the European Society of Cardiology. All rights reserved. © The Author(s) 2016. For permissions, please e-mail: journals.permissions@oxfordjournals.org".

On the right, the text "Open Research Knowledge Graph" is written next to a stylized atom or network icon.

# Our Objective

- To structure, in a fine-grained manner, knowledge elements from unstructured scholarly articles as a Knowledge Graph



Open  
Research  
Knowledge  
Graph

---

## Our Objective

- **Contributions Scholarly Knowledge. Structured.**
  - Focus on structuring only *contributions* from **natural language processing (NLP) articles**

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  - Focus on structuring only *contributions* from **natural language processing (NLP) articles**
- **Devise an annotation methodology:** NLPContributions

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2. ingest the resulting pilot annotated data into the Open Research Knowledge Graph (ORKG) infrastructure as a showcase to **automatically process the digitalized scholarly contribution knowledge elements.**
  - The ORKG<sup>1</sup> is a next-generation digital library infrastructure for machine-actionable knowledge content in scholarly articles.

**Reference:**

1. Jaradeh, Mohamad Yaser, et al. "Open research knowledge graph: next generation infrastructure for semantic scholarly knowledge." *Proceedings of the 10th International Conference on Knowledge Capture*. 2019.

---

## Plan for the Talk

- **NLPContributions Model**
- **The NLPContributions Annotation Guidelines**
- **Pilot Annotated Dataset Characteristics**
- **NLPContributions in the Open Research Knowledge Graph**

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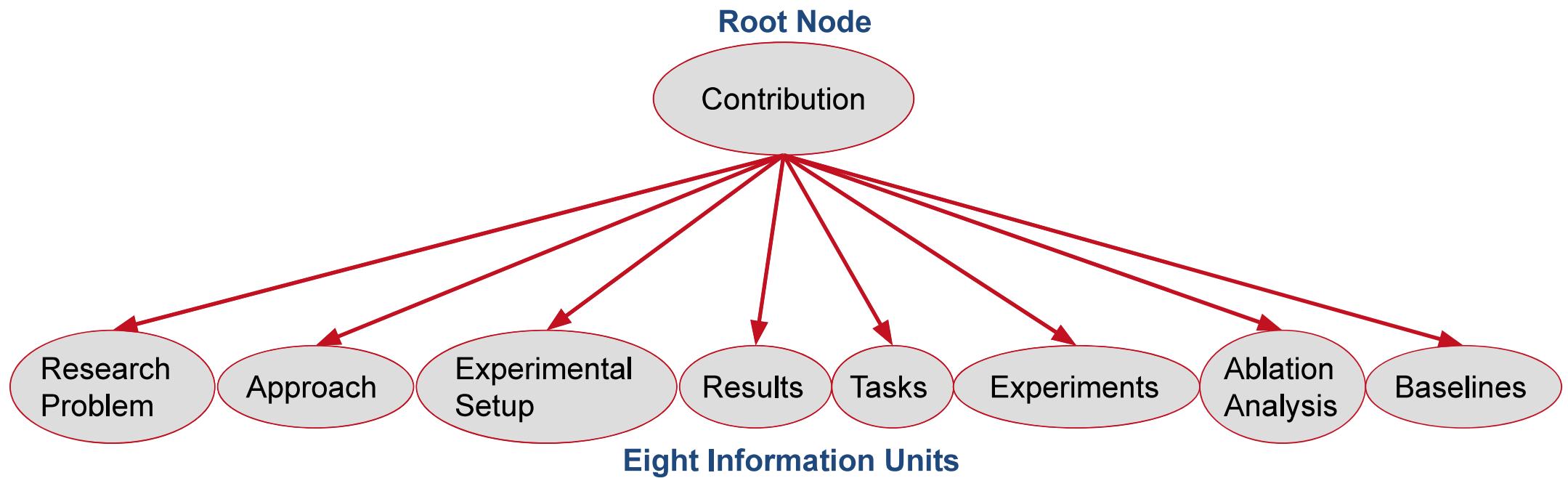
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  - a root node called Contribution,
  - eight first level nodes representing core information units under which the scholarly contributions data is organized
    - inspired from sectional information organization in scholarly articles

## NLPContributions Model: Core Skeleton



## NLPContributions Model: 8 Information Units

- Inspired from sectional information organization in scholarly articles
  1. ResearchProblem
  2. Approach
  3. ExperimentalSetup
  4. Results
  5. Tasks
  6. Experiments
  7. AblationAnalysis
  8. Baselines

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- involves annotating one or more sentences and precisely the research problem phrase boundaries in the sentences

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### 2. Approach

- solution proposed for the research problem
- connected to root by predicate *has*
- alternatively called Model or Method or Architecture or System or Application
- typically found in the article's Introduction section in the context of cue phrases such as "we take the approach," "we propose the model," "our system architecture," or "the method proposed in this paper."
  - exception: the first few lines within the main system description content in the article

## NLPContributions Model: 8 Information Units

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### 3. Experimental Setup

- details about the platform including both hardware (e.g., GPU) and software (e.g., Tensorflow library) for implementing the machine learning solution; and of variables, that determine the network structure (e.g., number of hidden units) and how the network is trained (e.g., learning rate), for tuning the software to the task objective

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- connected to root by predicate *has*
- found in the sections called Experiment, Experimental Setup, Implementation, Hyperparameters, or Training

## NLPContributions Model: 8 Information Units

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### 4. Results

- main findings or outcomes reported in the article for the research problem

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### 4. Results

- main findings or outcomes reported in the article for the research problem
- connected to root by predicate *has*
- found in an article's Results, Experiments, or Tasks sections
  - while the results are often highlighted in the Introduction, unlike the Approach unit, in this case, we annotate the dedicated, detailed section on Results because results constitute a primary aspect of the contribution.

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### 5. Tasks

- the Approach, particularly in multi-task settings, are tested on more than one task, in which case, all the experimental tasks are listed

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### 5. Tasks

- the Approach, particularly in multi-task settings, are tested on more than one task, in which case, all the experimental tasks are listed
- connected to root by predicate *has*
- is an encapsulating information unit
  - can include one or more of the ExperimentalSetup, Hyperparameters, and Results as sub information units

## NLPContributions Model: 8 Information Units

- Inspired from sectional information organization in scholarly articles
  1. ResearchProblem
  2. Approach
  3. ExperimentalSetup
  4. Results
  5. Tasks
  6. **Experiments**
  7. **AblationAnalysis**
  8. **Baselines**

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- is an encapsulating information unit
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### 6. Experiments

- is an encapsulating information unit
  - can be a combination of ExperimentalSetup and Results; or lists of Tasks and their Results; or Approach, ExperimentalSetup and Results combined
- particularly relevant in the content of multitask systems such as BERT
  - modeling ExperimentalSetup with Results or Tasks with Results is necessary in such systems since the experimental setup often changes per task producing a different set of results

## NLPContributions Model: 8 Information Units

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### 7. Ablation Analysis

- describes the performance of components in systems

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- describes the performance of components in systems
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### 7. AblationAnalysis

- describes the performance of components in systems
- a form of the results which are relevant to a Contribution
- typically found in sections with Ablation in the title, otherwise also in the running text

## NLPContributions Model: 8 Information Units

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### 8. Baselines

- a list of systems that a proposed approach is compared against

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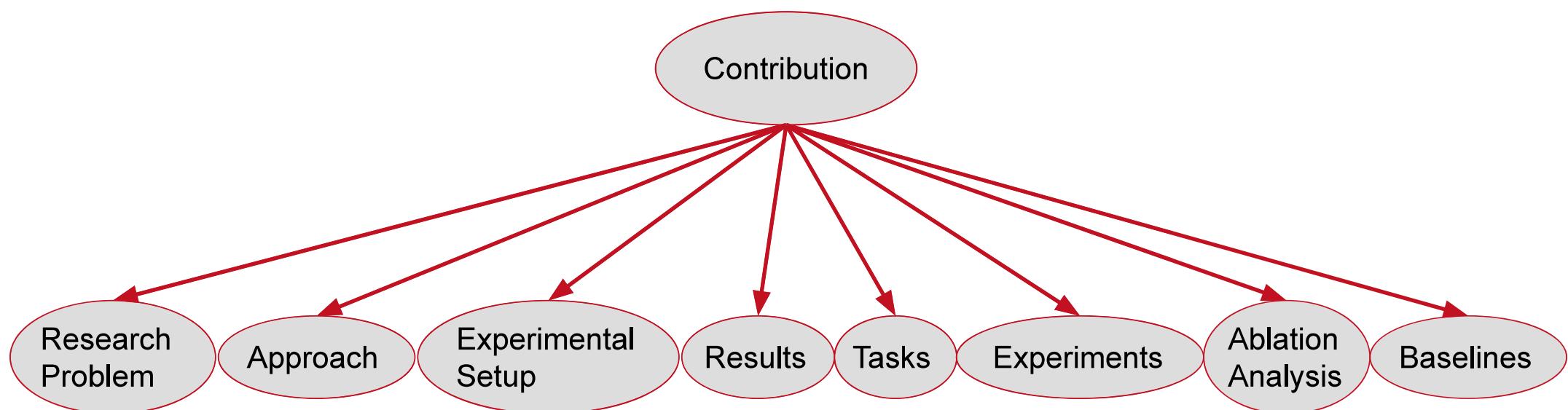
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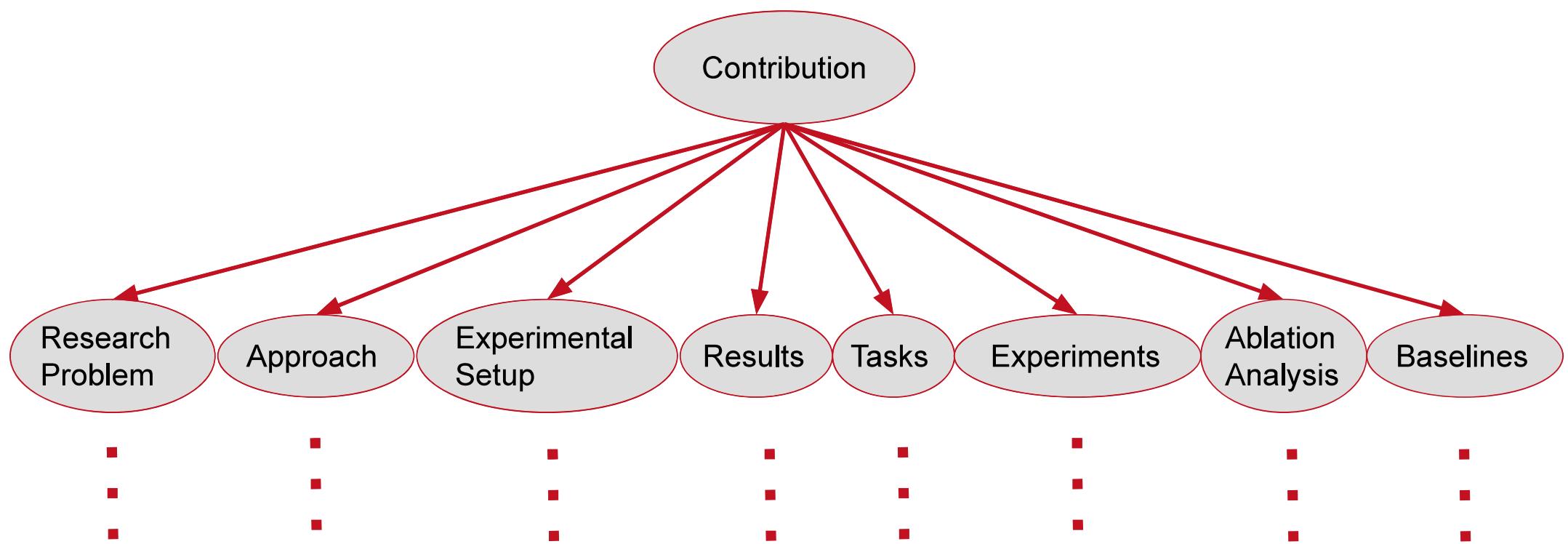
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## NLPContributions Model: 8 Information Units



## NLPContributions Model: Data Elements



## How to: Knowledge Graph building from Unstructured Text

- Given a paragraph(s) of unstructured text
  - identify the elements to model:
    - depends on:
      1. if the knowledge graph has an overarching knowledge theme
      2. or, if the knowledge nodes are to be of a certain type (e.g., scientific entities)
    - 1 subsumes 2
  - For 1 (our contributions-themed model):
    - identify the sentences that reflect the theme
    - identify the knowledge entities and predicates from the sentence of interest to the knowledge theme (e.g., scientific entities)
    - create subject-predicate-object triples toward RDFized KGs
    - ...

## NLPContributions Model: Data Elements



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- **Contribution Sentences**

- select candidate contribution sentences under each of the aforementioned 3 or more applicable information units (viz., ResearchProblem, Approach, Results, AblationAnalysis, etc.).

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- **Scientific Term and Predicate Phrases as Knowledge Entities (Graph Nodes)**
  - select phrases with an implicit understanding of whether they take the subject, predicate, or object roles in a per-triple context
- **Create Triples in Contribution Sequences**
  - relating phrases in subject, predicate, and object roles within triples
  - creating contribution sequences by using an object in one triple as the subject in another triple

## NLPContributions Model: Data Elements

Next: Example modeling data elements under an information unit

## NLPContributions Model: Approach Data Elements

```
{  
    "has" : {  
        "Approach" : {  
            "converting questions" : {  
                "to (un-interpretable) vectorial representations" : {  
                    "which require" : "no pre-defined grammars or lexicons",  
                    "can query" : {  
                        "any KB" : {  
                            "independent of" : "schema"  
                        }  
                    }  
                },  
                "from sentence" : "In this paper, we instead take the  
                    approach of converting questions to (un-interpretable)  
                    vectorial representations which require no pre-defined  
                    grammars or lexicons and can query any KB independent of  
                    its schema."  
            }  
        }  
    }  
}
```

**Reference:** Bordes, Antoine, Jason Weston, and Nicolas Usunier. "Open question answering with weakly supervised embedding models." *Joint European conference on machine learning and knowledge discovery in databases*. Springer, Berlin, Heidelberg, 2014.

## NLPContributions Model: ExperimentalSetup Data Elements

```
{  
    "has" : {  
        "Experimental setup" : {  
            "used" : [  
                {  
                    "BERTBase model" : {  
                        "pre-trained for" : "1M steps",  
                        "pre-trained on" : ["English Wikipedia",  
                            "BooksCorpus"]  
                    },  
                    "from sentence" : "We used the BERTBASE model  
                        pre-trained on English Wikipedia and  
                        BooksCorpus for 1M steps."  
                },  
                {  
                    "NVIDIA V100 (32GB) GPUs" : {  
                        "used" : {  
                            "eight" : {  
                                "for" : "pre-training"  
                            }  
                        },  
                        "from sentence" : "We used eight NVIDIA V100  
                            (32GB) GPUs for the pre-training."  
                    }  
                }  
            ]  
        }  
    }  
}
```

**Reference:** Lee, Jinhyuk, et al. "BioBERT: a pre-trained biomedical language representation model for biomedical text mining." *Bioinformatics* 36.4 (2020): 1234-1240.

## NLPContributions Model: Result Data Elements

```
{  
    "CoNLL test set" : {  
        "for" : {  
            "NER" : {  
                "F1-score" : "91.57%"  
            }  
        },  
        "from sentence" : "For NER (Table 7), S-LSTM  
                           gives an F1-score of 91.57% on the CoNLL  
                           test set, which is significantly better  
                           compared with BiLSTMs."  
    }  
}
```

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## NLPContributions Annotation Guidelines



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2. *Inferring Predicates*
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3. *How are lists modeled within contribution sequences?*
  - list items are treated just as sentences

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      - machine translation, named entity recognition, question answering, relation classification, and text classification.
- **Annotation Tools**
  - <https://jsoneditoronline.org/> - For JSON syntax checks
  - <https://www.orkg.org/> - As a litmus test for contributions-themed KG and as the Digital Library infrastructure to populate with the annotated KGs

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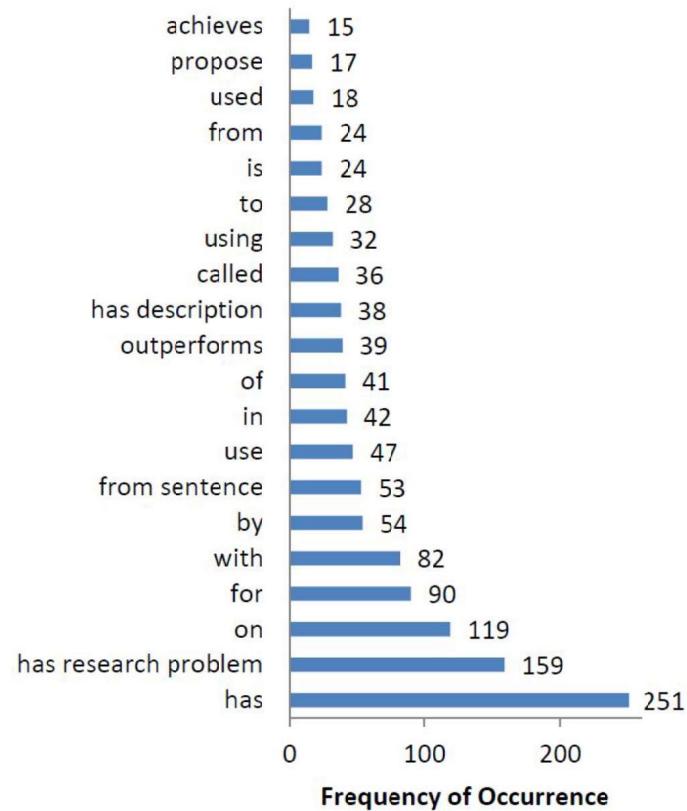
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Computer Science > Computation and Language

[Submitted on 26 Sep 2018]

## Graph Convolution over Pruned Dependency Trees Improves Relation Extraction

Yuhao Zhang, Peng Qi, Christopher D. Manning

Dependency trees help relation extraction models capture long-range relations between words. However, existing dependency-based models either neglect crucial information (e.g., negation) by pruning the dependency trees too aggressively, or are computationally inefficient because it is difficult to parallelize over different tree structures. We propose an extension of graph convolutional networks that is tailored for relation extraction, which pools information over arbitrary dependency structures efficiently in parallel. To incorporate relevant information while maximally removing irrelevant content, we further apply a novel pruning strategy to the input trees by keeping words immediately around the shortest path between the two entities among which a relation might hold. The resulting model achieves state-of-the-art performance on the large-scale TACRED dataset, outperforming existing sequence and dependency-based neural models. We also show through detailed analysis that this model has complementary strengths to sequence models, and combining them further improves the state of the art.

Comments: EMNLP 2018. Code available at: [this https URL](https://github.com/zhengqianzhang/EMNLP2018)

Subjects: Computation and Language (cs.CL)

Cite as: arXiv:1809.10185 [cs.CL]

(or arXiv:1809.10185v1 [cs.CL] for this version)

## Bibliographic data

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## Submission history

From: Yuhao Zhang [view email]

[v1] Wed, 26 Sep 2018 18:49:07 UTC (411 KB)

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Browse v0.3.3.5 released 2020-03-27

### Feedback?

## Abstract

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2018

Information Science

Yuhao Zhang

Peng Qi

Christopher D Manning

Published in: *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*

### Contribution 1

Research problems

 Add to comparison

Relation extraction

### Contribution data

Has

[Ablation analysis](#)[Baseline Models](#)[Model](#)[Results](#)Accessible at <https://www.orkg.org/orkg/paper/R44287>

## Abstract

Dependency trees help relation extraction models capture long-range relations between words. However, existing dependency-based models either neglect crucial information (e.g., negation) by pruning the dependency trees too aggressively, or are computationally inefficient because it is difficult to parallelize over different tree structures. We propose an extension of graph convolutional networks that is tailored for relation extraction, which pools information over arbitrary dependency structures efficiently in parallel. To incorporate relevant information while maximally removing irrelevant content, we further apply a novel pruning strategy to the input trees by keeping words immediately around the shortest path between the two entities among which a relation might hold. The resulting model achieves state-of-the-art performance on the large-scale TACRED dataset, outperforming existing sequence and dependency-based neural models. We also show through detailed analysis that this model has complementary strengths to sequence models, and combining them further improves the state of the art.

## Graph Convolution over Pruned Dependency Trees Improves Relation Extraction

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## Plan for the Talk

- NLPContributions Model
- The NLPContributions Annotation Guidelines
- Pilot Annotated Dataset Characteristics
- NLPContributions in the Open Research Knowledge Graph

## Conclusion: Takeaways

- Scholarly work can be realized as expressions other than an article
  - We proposed the **NLPContributions annotation model to create contributions-themed knowledge graphs**

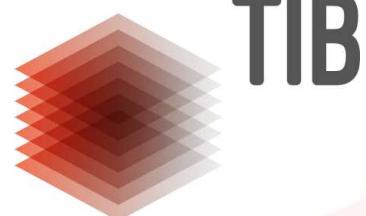
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- The NLPContributions annotation scheme can be leveraged to annotate a larger dataset (of a few hundreds of articles)
  - Train machine-learning-based automated machine readers to annotate tens of thousands of articles for contributions-based KG data which is humanly impossible to do

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**Thank you for your attention!**

Questions?