



Mining Acknowledgement Texts in Web of Science (MinAck)

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Background and objectives

english linguistics

The focus of our project MinAck is the detection and quantitative analysis of acknowledged entities, i.e., named entity recognition (NER) task in a larger corpus of Web of Science (WoS) articles, which include acknowledgements.

Why Acknowledgments?

may give an insight on reward systems, collaboration structures, and hidden research trends in scientific community (Giles & Councill, 2004)

can help the reader to better understand the setup and framing of a given scientific text

analysis interesting their automatic poses research and methodological problems

NLP tool:

FLAIR framework for state-of-the-art NLP (Akbik et al., 2019).

Project steps:

Step 1. Create datasets: define the disciplines and gather the acknowledgement texts from WoS.

- > 2 training corpora (50 and 300 entries)
- > 1 acknowledgments corpus (200,000 entries, i.e., 50,000 from each of the 4 scientific domains)

Records from:

- > four different scientific disciplines (sociology, economics, oceanography, computer science)
- published from 2014 to 2019
- WoS records types "article" and "review"

Step 2. Annotate the training data for the FLAIR NLP Framework.

6 entity types were defined:

IND: person

FUND: funding organization **GRNB**: grant number

UNI: university **COR** : corporation **MISC**: miscellaneous

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Annotated corpus:

id	txt	GRNB	FUND	IND	UNI	COR	MISC
	Scott Griffiths is supported by an Australian	1121538	Australian National Health and	Scott Griffiths			
	National Health and Medical Research		Medical Research Council Early				
	Council Early Career Fellowship (grant		Career Fellowship				
	number: 1121538).						
	This research was supported by the	13042				Oesterreichische	
	Oesterreichische Nationalbank,					Nationalbank,	
	Anniversary Fund (Project No. 13042).					Anniversary Fund	
	The author would like to express her	SoTL: 0152AA-A09			Center of Excellence in		Scholarship of
	gratitude to the Center of Excellence in				Teaching and		Teaching and Learning
	Teaching and Learning (CETaL), UTP for				Learning;CETaL;UTP		
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	grant for this study.						

Flair corpus format

Scott B-IND Griffiths I-IND is O supported 0 by 0 an O Australian B-FUND National I-FUND Health I-FUND and I-FUND Medical I-FUND

A semi-automated annotation approach was developed.

training Two corpora, containing possibly equal of amount of entities types were created.

effectiveness The corpuses of different sized will be tested on different training algorithms.

Step 4. Analysis with the best FLAIR model.

Step 5. Aggregating the results.

Step 3. (in progress) Train the FLAIR with the training datasets and define the best model and training algorithm.

A small dataset (50 sentences) was tested with three FLAIR training algorithms:

- NER Model with Flair Embeddings
- NER Model with Transformers
- Zero-shot NER Model (TARS)

Training results:





