Label Propagation for Tax Law Thesaurus Extension

Markus Müller, 04.06.2018, Master’s Thesis Kick-Off Presentation

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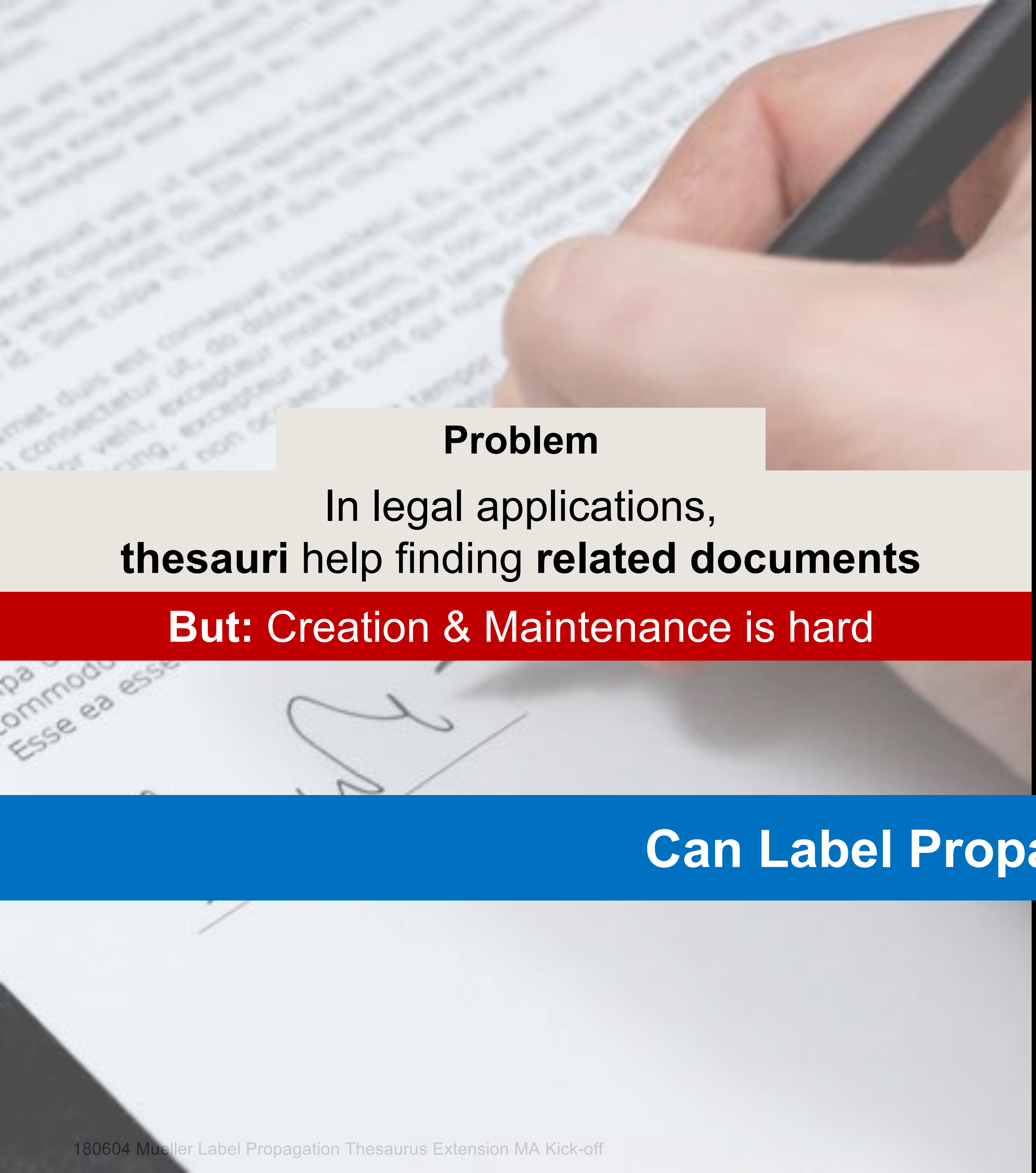


Problem

In legal applications,
thesauri help finding **related documents**

But: Creation & Maintenance is hard

Technology

Label Propagation can find communities in graphs
semi-supervised learning

Can Label Propagation help us?

Outline

Motivation

- Problem: Thesauri in the Legal Context
- Opportunity: Label Propagation on Graphs
- Related Work

Research Questions

Research Approach

- Technology Flow
- Concept
- Challenges

Timeline

Motivation

Problem: Thesauri in the Legal Context

What is a Thesaurus?

A Collection of Synonym Sets (Synsets)

{ example, instance, model, case, illustration, lesson, object, part, pattern, precedent, symbol,… }

Can contain other relations between words,
e.g. broader terms, narrower terms, top term, antonyms

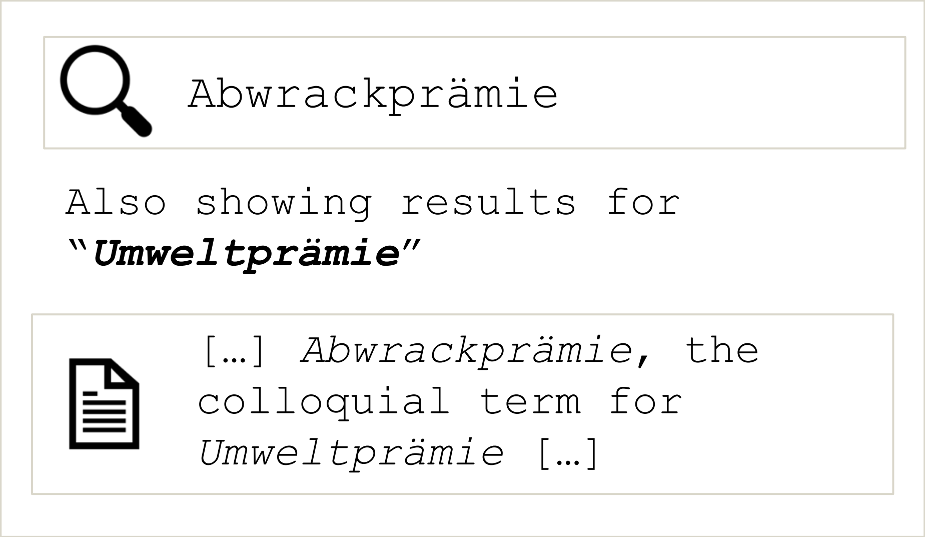
Example from Thesaurus.com

Motivation

Problem: Thesauri in the Legal Context

Why are Thesauri useful, especially in the Legal Domain?

Thesauri enhance Search
Search Query Expansion



Abwrackprämie

Also showing results for "***Umweltprämie***"

[…] *Abwrackprämie*, the colloquial term for *Umweltprämie* […]

Legal work deals with lots of texts

Laws, past cases, comments on laws…

Legal Content Providers
need to create & maintain thesauri

Wolters Kluwer 2016 [1]: "***Legal Thesauri*** *are the* ***backbone*** *of many application features in JURION*"

[1] C. Dirschl, "Thesaurus Generation and Usage at Wolters Kluwer Deutschland GmbH," *Jusletter IT 25. Februar 2016*, Feb. 2016.

Motivation

Problem: Thesauri in the Legal Context

Creating and Maintaining a Thesaurus is hard

Wolters Kluwer 2016 [1]:

“*Thesaurus creation is a very challenging task*”

“*do not aim for having one single thesaurus in place […], but to have smaller, domain specific thesauri*” (e.g. tax law, tenancy law,…)

For each thesaurus:

- “*1 to 2 person months internal effort”*
- “*10 to 20k€ external costs*”
- “*Normally there are no processes for [maintenance] in place*“

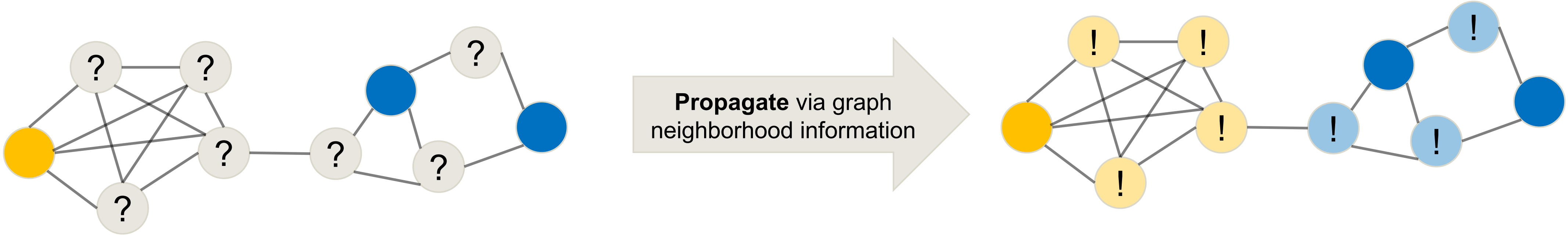
[1] C. Dirschl, “Thesaurus Generation and Usage at Wolters Kluwer Deutschland GmbH,” *Jusletter IT 25. Februar 2016*, Feb. 2016.

Motivation

Opportunity: Label Propagation on Graphs

Label Propagation

Family of **semi-supervised** machine learning methods
Use **few labeled** records & **graph structure**
to label a **large unlabeled** dataset



Very good **performance**, even with large datasets and lots of labels

Can we apply Label Propagation to
find new Synonyms?

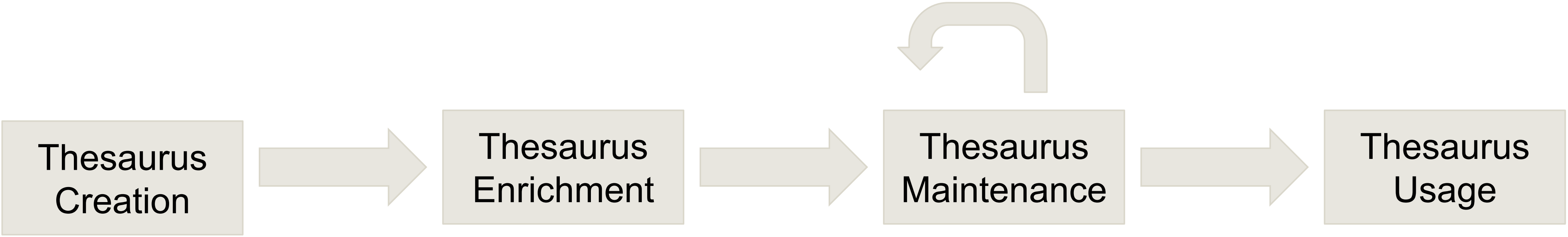
where Label ≙ Synset

Motivation

Opportunity: Label Propagation on Graphs

Process around Thesauri [1]

Process [1]



LP Opportunities

semi-automation

- *Suggest additions to manually created synsets*
- *Suggest new synsets*

thesauri linkage

Suggest relations between synsets of different thesauri

semi-automation, quality assurance

Suggest synset adjustments

[1] C. Dirschl, “Thesaurus Generation and Usage at Wolters Kluwer Deutschland GmbH,” *Jusletter IT 25. Februar 2016*, Feb. 2016.

Motivation
Related Work

Previous Research on **Thesaurus Extension** at sebis

[2] J. Landthaler, B. Waltl, D. Huth, D. Braun, and F. Matthes, “Extending Thesauri Using Word Embeddings and the Intersection Method,” 2018.

Research on **Label Propagation** & its **Application**

[3] S. Ravi and Q. Diao, “Large Scale Distributed Semi-Supervised Learning Using Streaming Approximation,” *arXiv:1512.01752 [cs]*, Dec. 2015.
[4] A. Kannan *et al.*, “Smart Reply: Automated Response Suggestion for Email,” *arXiv:1606.04870 [cs]*, Jun. 2016.
[5] X. Zhu and Z. Ghahramani, “Learning from labeled and unlabeled data with label propagation,” 2002.
[6] Y. Bengio, O. Delalleau, and N. Le Roux, “Label Propagation and Quadratic Criterion,” *Semi-Supervised Learning*, Sep. 2006.

Cooperation with Prof. Günnemann
Data Mining and Analytics Group

[7] W. Gatterbauer, S. Günnemann, D. Koutra, and C. Faloutsos, “Linearized and Single-pass Belief Propagation,” *Proc. VLDB Endow.*, vol. 8, no. 5, pp. 581–592, Jan. 2015.
[8] D. Eswaran, S. Günnemann, C. Faloutsos, D. Makhija, and M. Kumar, “ZooBP: Belief Propagation for Heterogeneous Networks,” *Proc. VLDB Endow.*, vol. 10, no. 5, pp. 625–636, Jan. 2017.

Research Questions

Is LP a **suitable technology** for thesaurus extension in the legal domain?

Can we **model the thesaurus extension problem** on the LP technology?

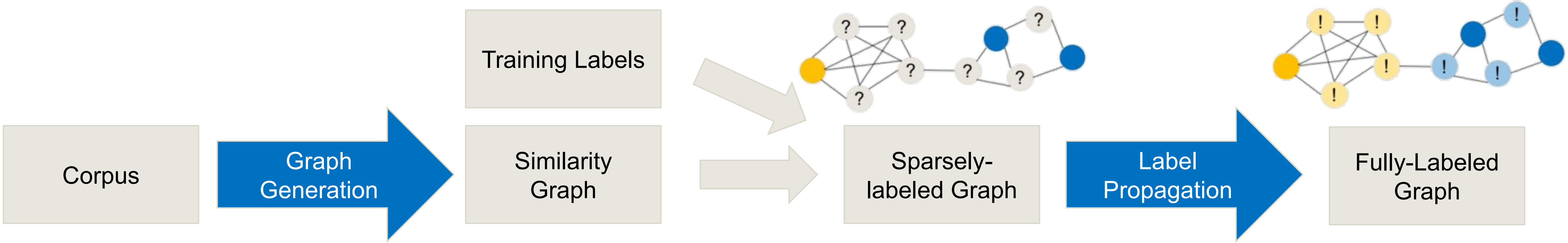
How can we get **semantic & context information into a graph** for LP?

How much **automation** for **thesaurus creation** is achievable with LP?

What LP **algorithms work best**?

Research Approach

Technology Flow



(from thesaurus by DATEV)

Training Labels

Corpus

Graph Generation

Similarity Graph

Sparsely-labeled Graph

Label Propagation

Fully-Labeled Graph

Tax Law Corpus provided by DATEV

Many options to try:

- Various word embeddings technologies
- Various hyper-parameters
- Various graph augmentation possibilities

Many options to try:

- Standard LP
- Label Spreading
- Belief Propagation
- Modifications by reference papers

⇒ Larger synsets than before

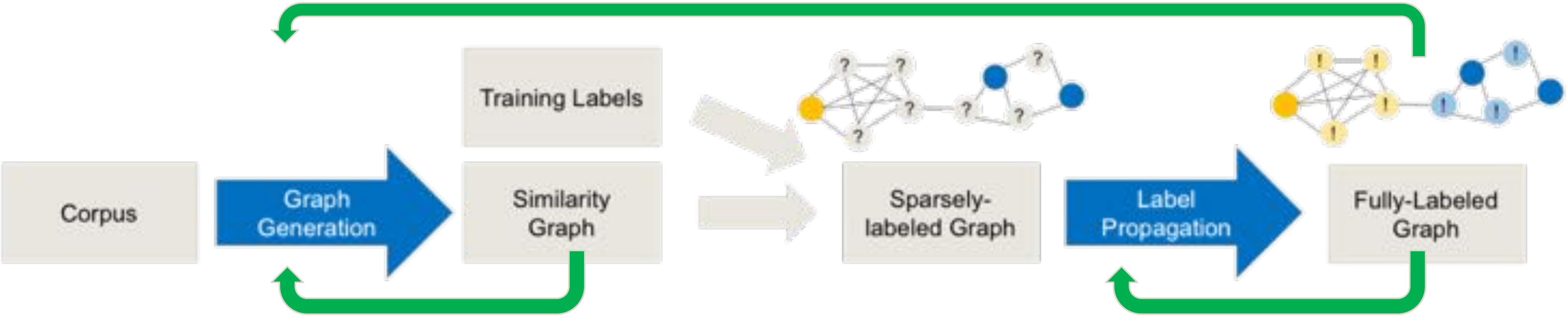
Research Approach

Concept

Build a framework for **iteratively** trying out many approaches

Evaluate

Continuous evaluation on corpus labels	**Continuous comparison** to baseline algorithms	**Manual review** by experts
Quantitative	*Quantitative*	*Qualitative*



Research Approach

Challenges

Analogy **Synset = Label**
might not work out of the box

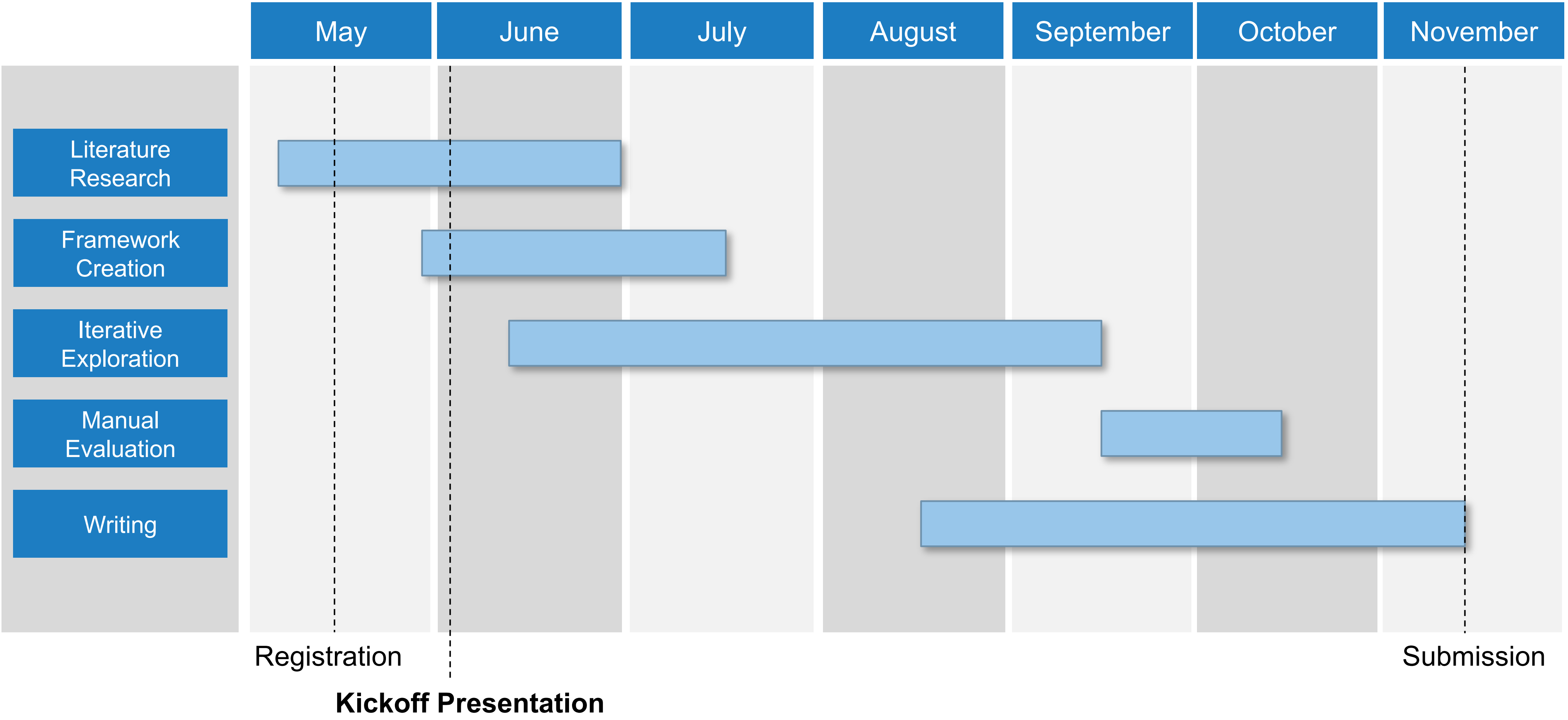
Many different options and approaches

Several aspects out of scope:

- compound words
- multi-label (multiple synsets/word)

Will it work on a **different corpus**?

Timeline


May
June
July
August
September
October
November
Literature Research
Framework Creation
Iterative Exploration
Manual Evaluation
Writing
Registration
Kickoff Presentation
Submission

References

[1] C. Dirschl, “Thesaurus Generation and Usage at Wolters Kluwer Deutschland GmbH,” *Jusletter IT 25. Februar 2016*, Feb. 2016.

[2] J. Landthaler, B. Waltl, D. Huth, D. Braun, and F. Matthes, “Extending Thesauri Using Word Embeddings and the Intersection Method,” 2018.

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Backup

Supervised, Semi-Supervised, Transductive

Supervised learning: Learn on labeled training instances, perform prediction on unknown test data.

Semi-supervised learning: Learn on labeled training instances and unlabeled training instances, perform prediction on unknown test data.

Transductive learning: Learn on labeled training instances and unlabeled training instances, perform prediction on known test [=training] data.

Chapter 6: Network Data, Mining Massive Datasets, Stephan Günnemann, WS 2016/17

Comment

In literature, propagation is often referred to as semi-supervised learning, but actually it is transductive learning. A solution would be to place both the inductive and the transductive approaches as categories of semi-supervised learning.

Backup

DATEV Corpus Stats

~130.000 separate texts

~140 Mio. words

~180.000 distinct words

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