

Matching with Transformers in MELT

Sven Hertling, Jan Portisch, Heiko Paulheim
University of Mannheim



Joint Work



Sven Hertling

Data and Web Science Group,
University of Mannheim
sven@informatik.uni-mannheim.de



Jan Portisch

Data and Web Science Group,
University of Mannheim / SAP SE
jan@informatik.uni-mannheim.de



Prof. Dr. Heiko Paulheim

Data and Web Science Group,
University of Mannheim
heiko@informatik.uni-mannheim.de

Agenda

- Motivation
- What is MELT
- Transformers in MELT
- Experiments
- Conclusion & Future Work

Motivation

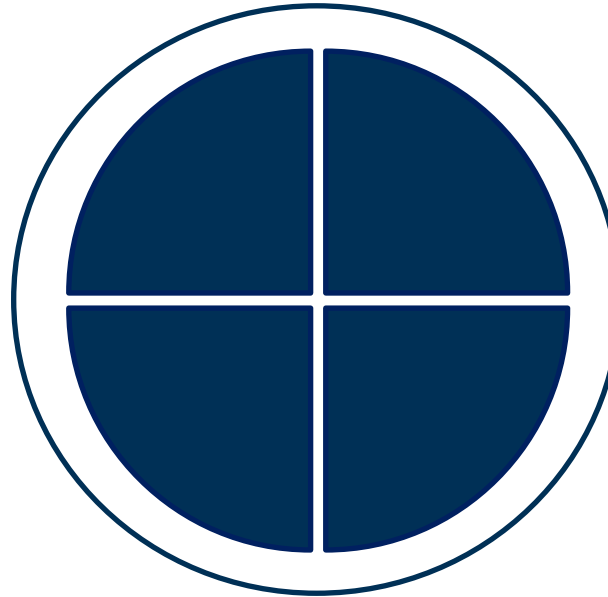
Motivation

- the transformer architecture achieved breakthrough results in various NLP domains
- this poses the question in how far transformers can be beneficial for the ontology matching domain

What is MELT?

What is MELT?

- **Easy** matcher development
- Re-Usable Matcher
Components
- **Non-Java** matcher
development
- **Maven** support
- Facilitate **matcher packaging**
(SEALS, HOBBIT, Docker
Web)
- Facilitate **matcher
submission**

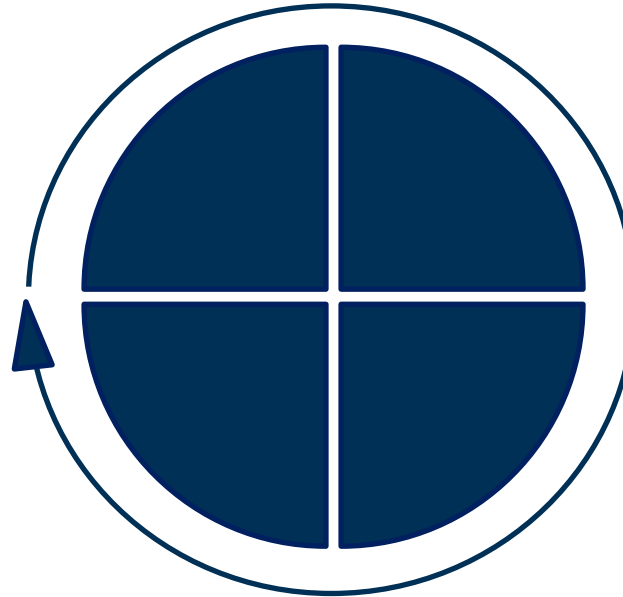


- Allow for **parameter
optimization**
- **Advanced evaluation** capabilities
- **Evaluation before packaging**
- Allow for **interactive visualization**
- **Streamlined** development process
- **Integration** with existing tooling
- **OAEI** support
- **Extensibility**

What is MELT?

Matcher
Development
with Transformers

Matcher
Submission



Matcher **Fine-**
Tuning

Matcher
Evaluation

There is MUCH more to MELT

Ontology **Caching** Services

Execution of **SEALS**,
HOBBIT, **WEB** packages
from within MELT

OAEI-Track Organizer
Tools

ExecutionResult
Indexing

One-Time **Auto-Download**
of OAEI Tracks

Matcher **Pipelining**

Multi-Threaded Matcher
Execution

TRY IT!



MELT @GitHub

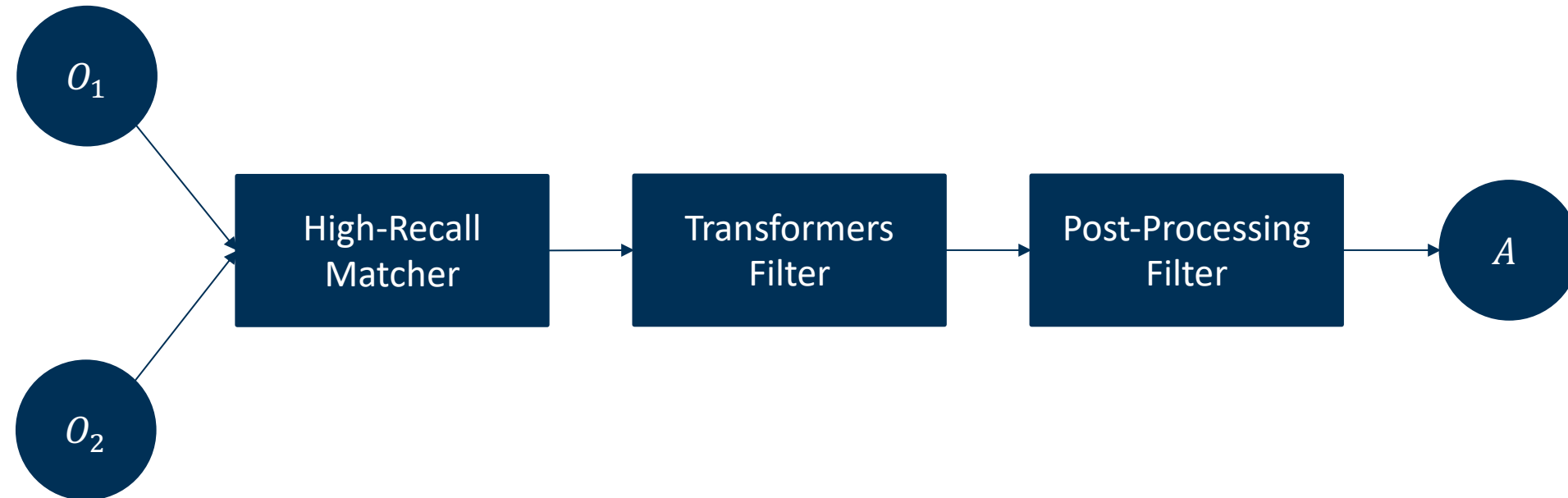
> **50** matchers

> **25** filters

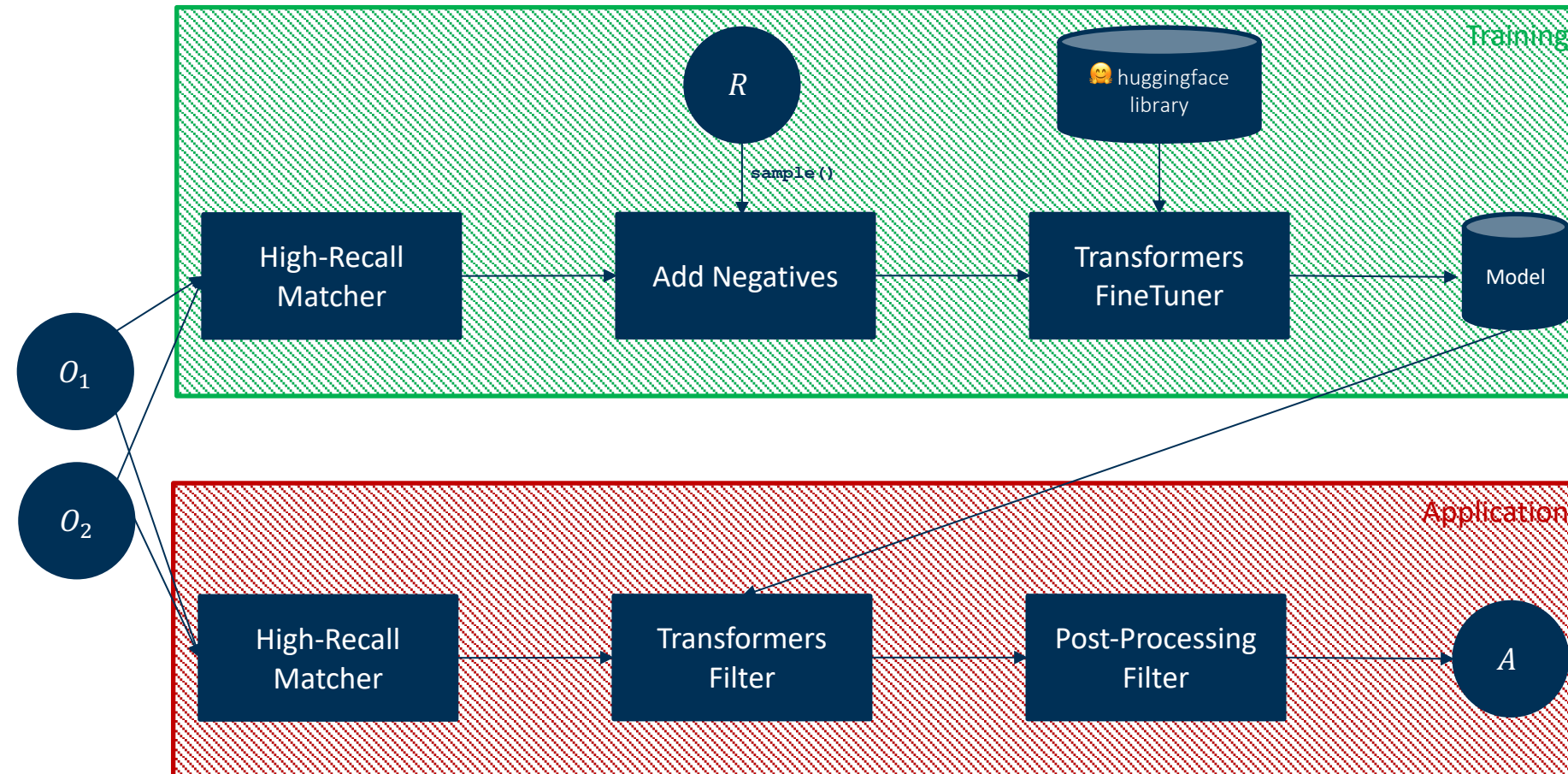
Alignment **Extensions**

Transformers in MELT

The Transformer Pipeline



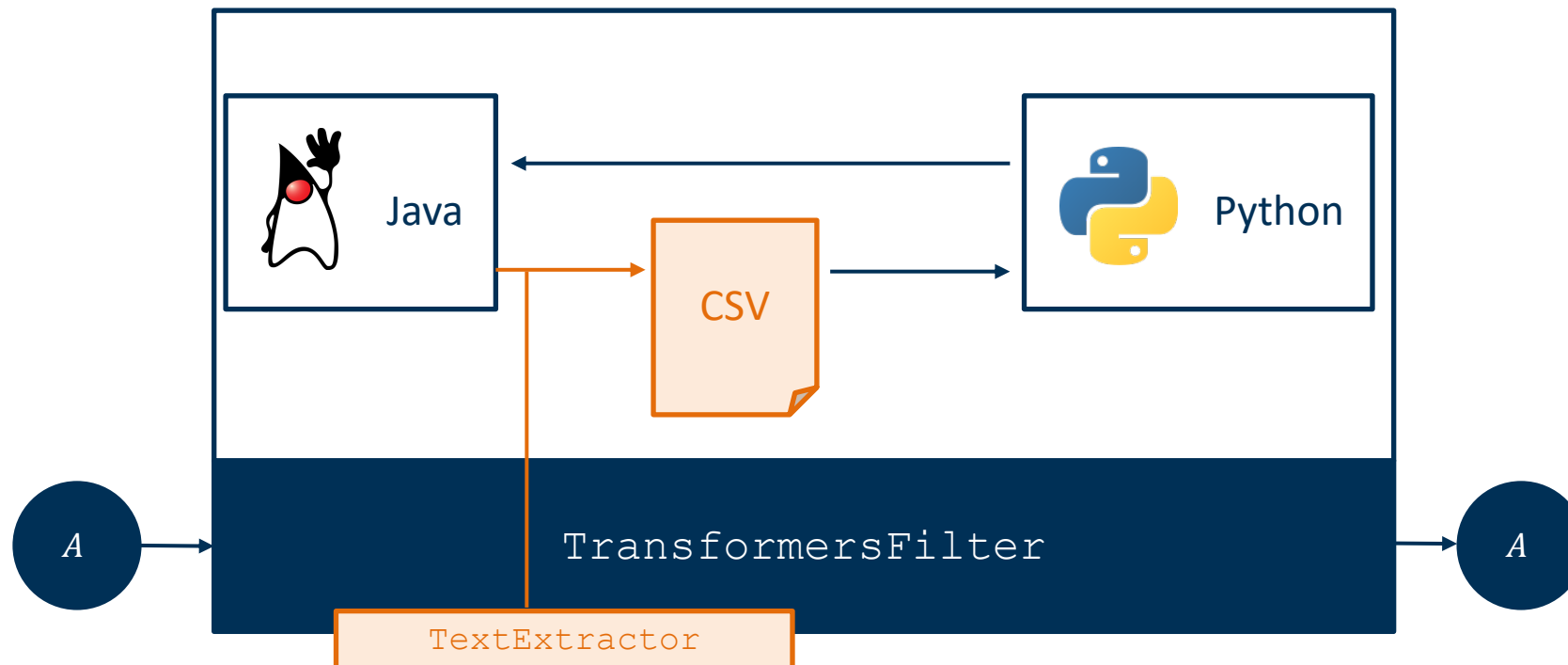
The Transformer Pipeline



Generating Negatives

- positives:
 - (1) reference
 - (2) high-precision system
- negatives
 - generate randomly (`AddNegativesRandomlyAbsolute`, `AddNegativesRandomlyShare`)
 - generate through one-to-one assumption, e.g. incomplete or unknown reference `AddNegativesRandomlyOneOneAssumption`
- all new strategies implement interface `AddNegatives`

TextExtractors & Technical Details



TextExtractors & Technical Details

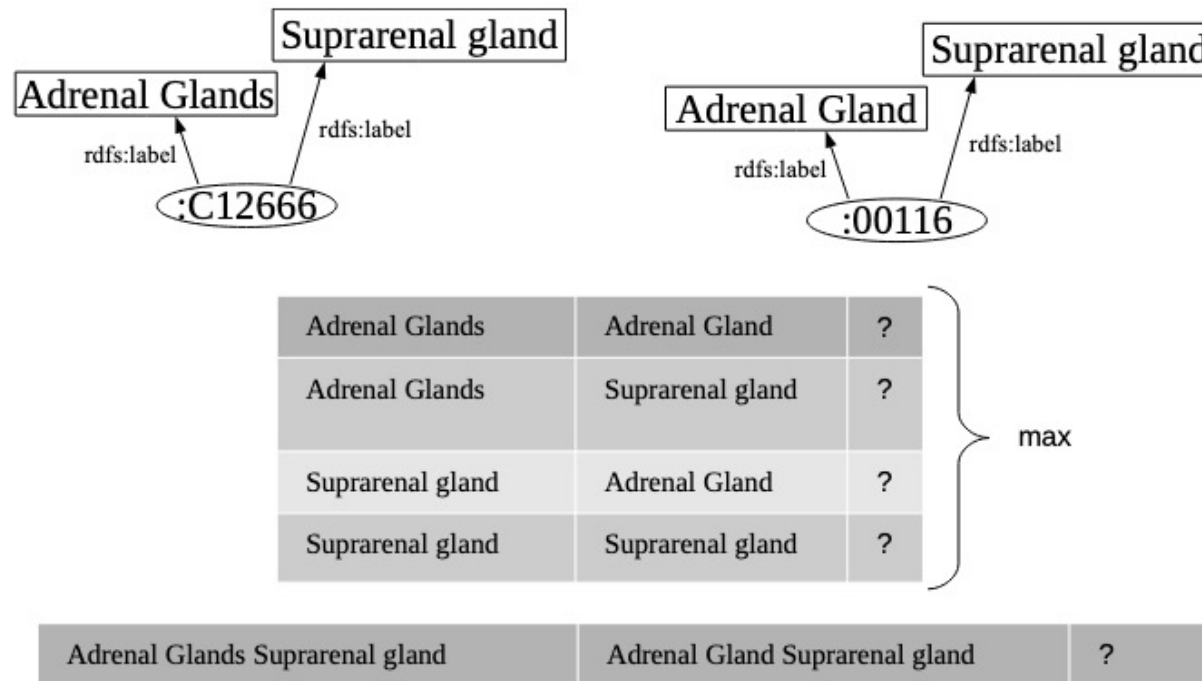


Fig. 2. Optional multi-text mechanisms implemented in class `TransformersFilter`.

Hyperparameter Optimization

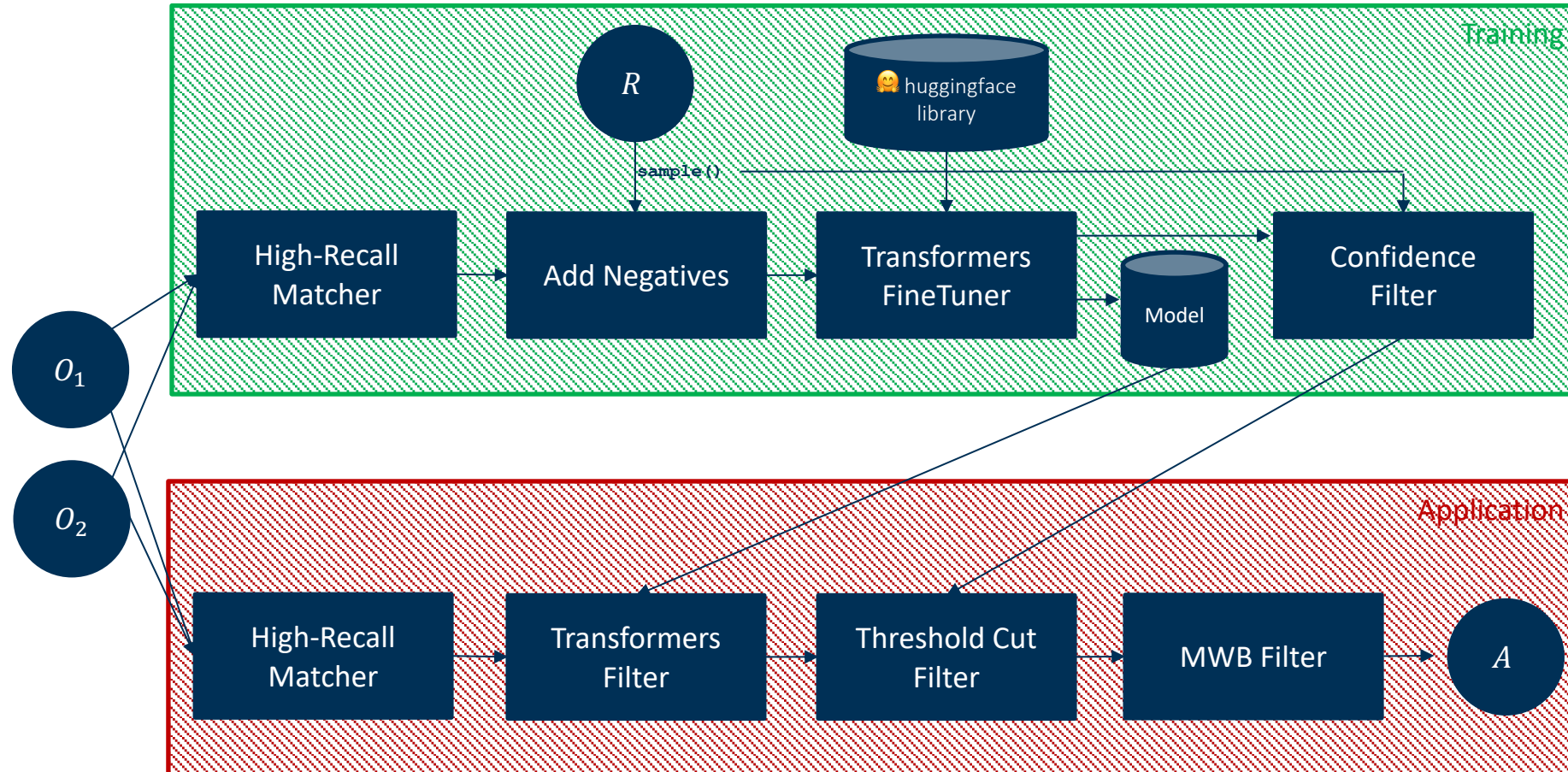
- via Ray Tune
- initial hyperparameter search space
 - learning rate: loguniform distribution between 10^{-6} and 10^{-4}
 - epochs: random choice between 1 and 5
 - seed: uniform distribution between 1 and 40
 - batch size: random choice of 4, 8, 16, 32, 64
(max size automatically determined)
- optimizable metrics: loss, accuracy, F1, recall, precision, AUC
- `class TransformersFineTunerHpSearch`

It's not complicated!

```
public class TransformerApplyExample extends MatcherPipelineYAAAJena {  
  
    @Override  
    protected List<MatcherYAAAJena> initializeMatchers() {  
        List<MatcherYAAAJena> list = new ArrayList<>();  
  
        // some recall matcher  
        list.add(new RecallMatcher());  
  
        // transformer filter  
        list.add(new TransformersFilter(  
            new TextExtractorAllLiterals(),  
            "albert-base-v2"));  
  
        // some post processing steps  
        list.add(new ConfidenceFilter(0.75));  
        list.add(new MaxWeightBipartiteExtractor());  
  
        return list;  
    }  
}
```

Experiments

Experiments | Pipeline



Experiments

- tracks: *Anatomy, Confernce, Knowledge Graph*
- with and without fine-tuning
- sampling rate: 20%
- models
 - bert-base-cased
 - roberta-base
 - albert-base-v2

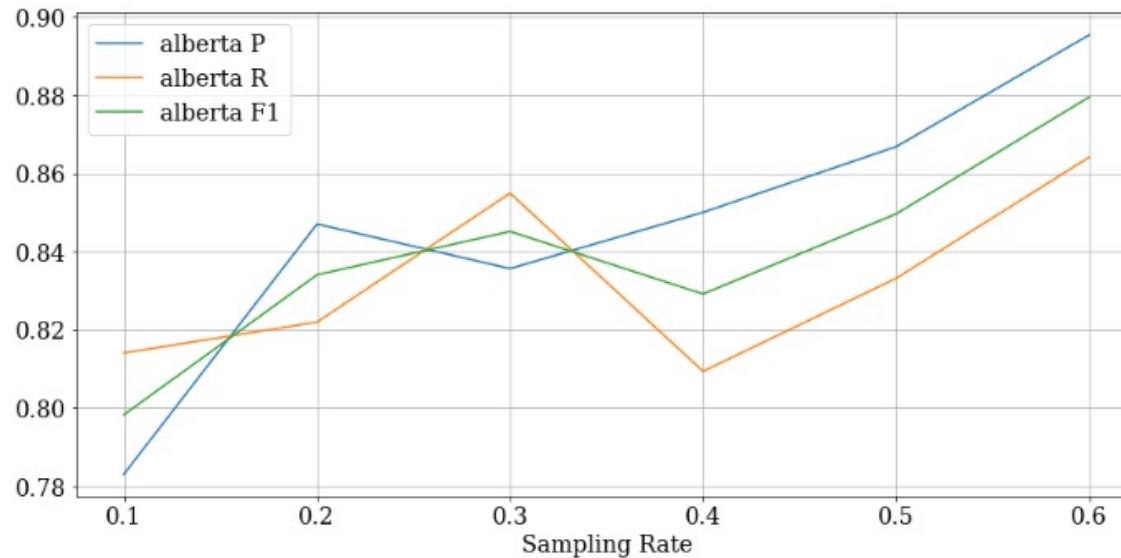
Results

		Conference			Anatomy			Knowledge Graph		
		P	R	F1	P	R	F1	P	R	F1
Baseline	SimpleString	0.710	0.498	0.586	0.964	0.708	0.816	0.909	0.727	0.808
	High Recall	0.450	0.561	0.179	0.037	0.942	0.071	0.167	0.915	0.283
Zero-Shot	bert-base-cased (mrpc-tuned)	0.650	0.548	0.594	0.531	0.817	0.644	0.739	0.714	0.726
Fine-Tuned (per Track)	bert-base-cased	0.748	0.361	0.487	0.726	0.689	0.707	0.941	0.789	0.859
	roberta-base	0.667	0.498	0.570	0.715	0.749	0.732	0.400	0.388	0.393
	albert-base-v2	0.812	0.397	0.533	0.854	0.825	0.839	0.687	0.665	0.676

Table 1. Results of non-fine-tuned and fine-tuned transformer models (multi-text) with 20% sampling from the reference alignment. As per OAEI customs, we report micro average scores for the conference and macro average scores for the KG track.

- fine-tuning increases performance
- albert-base-v2 and bert-base-cased achieved best results
- minor improvements through hyperparameter tuning

Results



- performance increases with increasing sample rate
- low sampling (10-20%) is sufficient for good results

Fig. 4. albert-base-v2 performance on the anatomy track using different reference sampling rates.

Conclusion and Future Work

Conclusion & Future Work

- Transformers for MELT allow the broad usage of transformers without deep technical skills (out-of-the-box components)
- Transformers are promising for the matching domain as shown in experiments
- in the future, we plan to
 - add further matching components (alignment repair)
 - include sentence transformers (transformers as matching component, not as filter)

Thank you.

Sven Hertling

University of Mannheim

<https://www.uni-mannheim.de/dws/people/researchers/phd-students/sven-hertling/>

sven@informatik.uni-mannheim.de

Jan Portisch

University of Mannheim / SAP SE

<https://www.jan-portisch.eu>

jan@informatik.uni-mannheim.de /
jan.portisch@sap.com

Heiko Paulheim

University of Mannheim

<http://www.heikopaulheim.de/>

heiko@informatik.uni-mannheim.de