Injecting Knowledge into Sentence Embedding Models for Information Retrieval using Adapters

Kick-Off Presentation

23.01.2023

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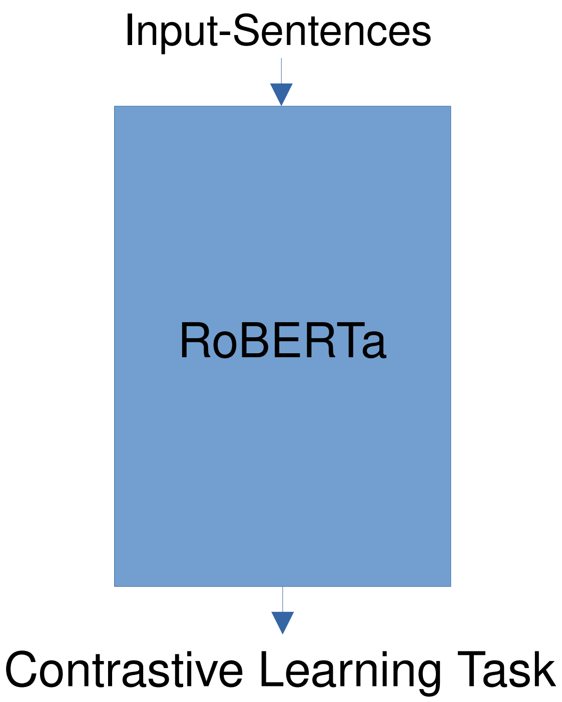
Outline

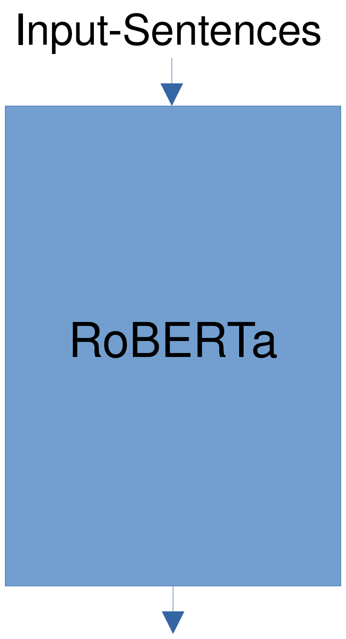
Motivation – Sentence Embedding Models

- Similarity comparison of sentences/texts
- Information Retrieval Tasks



Motivation – Adapters

- Pretrained once, „Plug'n'Play“ for different use cases
- Lower training time due to less parameters



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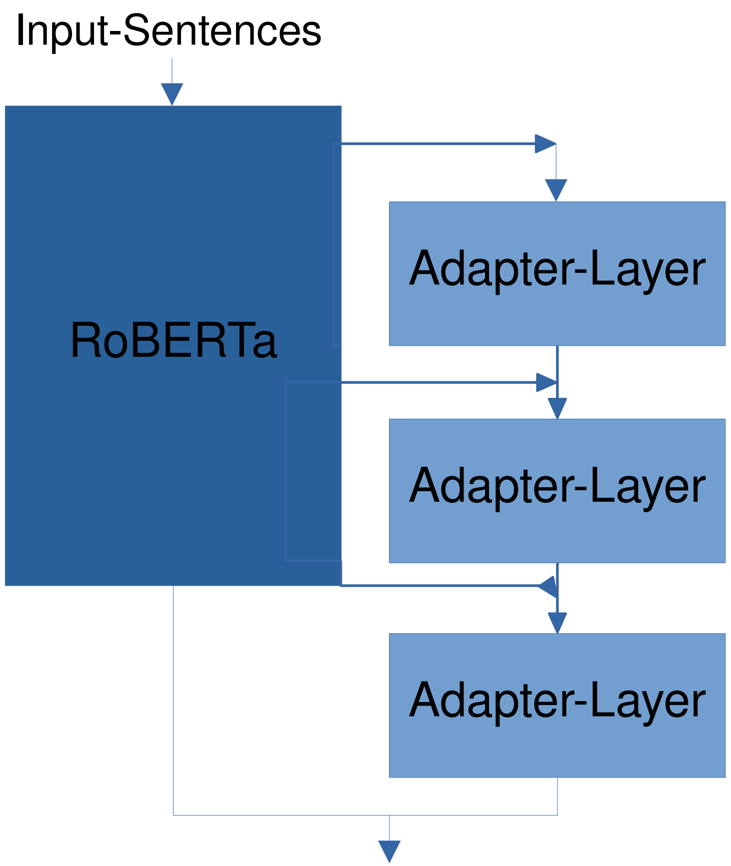


Problem Statement

- Sentence Embedding Models fail to encode factual knowledge [1]
- Enhance Sentence Embedding Models by injecting Knowledge through Adapters
    - Inject structured knowledge from Knowledge Graphs
- SotA: Contrastive Learning

Methodology – Injecting Knowledge

RQ1: How to inject structured Knowledge into Sentence Embedding models with adapters?

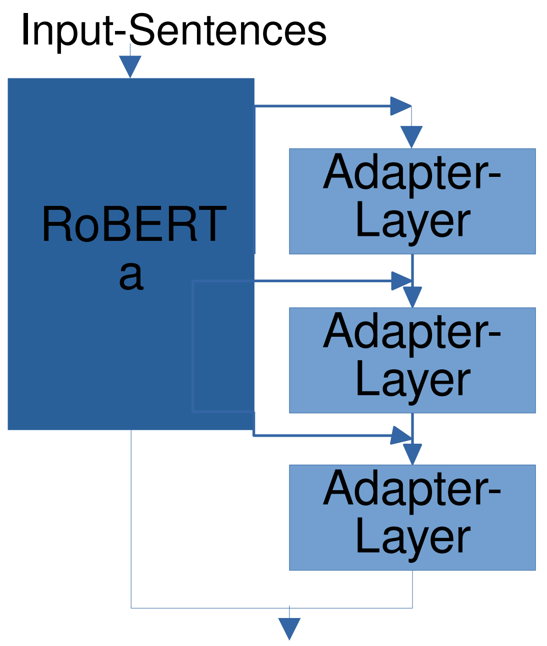
- Learning methods for Adapters
  - Contrastive Learning of Graph-based data
    - Anchor: (--, relation, target_a) „Amazon is an American tech company.“
    - Pos: (--, relation, target_a) „Facebook is an American tech company.“
    - Neg: (--, relation, target_b) „Mercedes-Benz is a German car manufacturer.“
  - Masked Language Modeling on Knowledge Graphs
    - (“Mercedes-Benz”, “is-a”, “car manufacturer”)
    - Mask out the object
    - Mercedes-Benz is a <MASK>

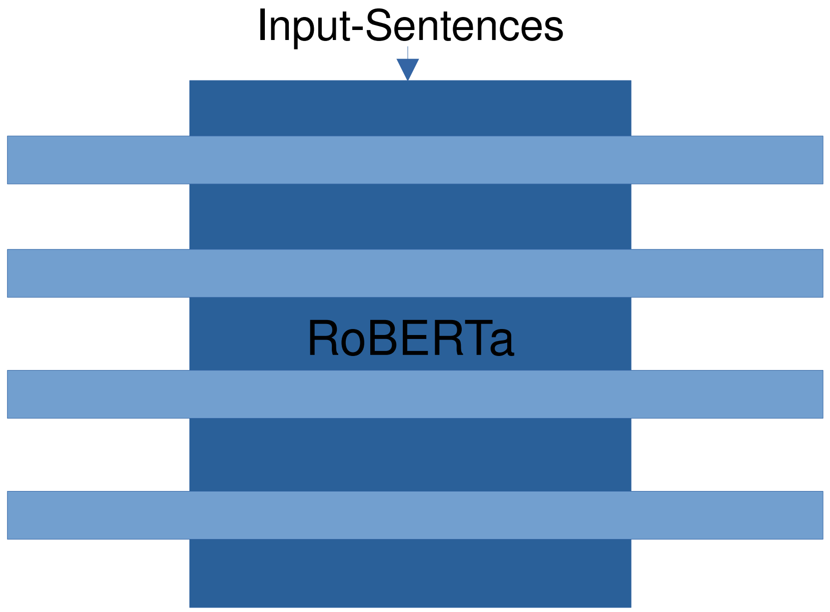
Methodology – Sentence Embedding Model Training

- Using SotA: SimCSE [2]
- Supervised SimCSE:
    - Contrastive Learning of Anchor, Positive, Negative Sentence
- Unsupervised SimCSE:
    - Contrastive Learning of Anchor, Dropout-Anchor, Different Sentence

Methodology – Adapter Architectures

- K-Adapter [1]
- Houlsby [3]
- ...





Preliminary Results

RQ2: Do Knowledge Adapters improve information retrieval tasks of Sentence Embedding models?

- K-Adapter (supervised SimCSE)
  - Adapter pretrained on different dataset, via Contrastive Learning
  - Resulting Knowledge-infused model trained on same dataset

Model	STS12	STS13	STS14	STS15	STS16	STSBenchmark	SICKRelatedness	Avg.
Roberta	76.33	87.36	82.10	86.03	83.82	86.35	80.69	83.24
K-Adapter	77.87	87.24	82.56	87.17	84.62	86.26	79.93	83.68

Preliminary Results

- K-Adapter (unsupervised SimCSE)
  - Adapter pretrained on different dataset, via Contrastive Learning (supervised)
  - Resulting Knowledge-infused model trained on same dataset (unsupervised)

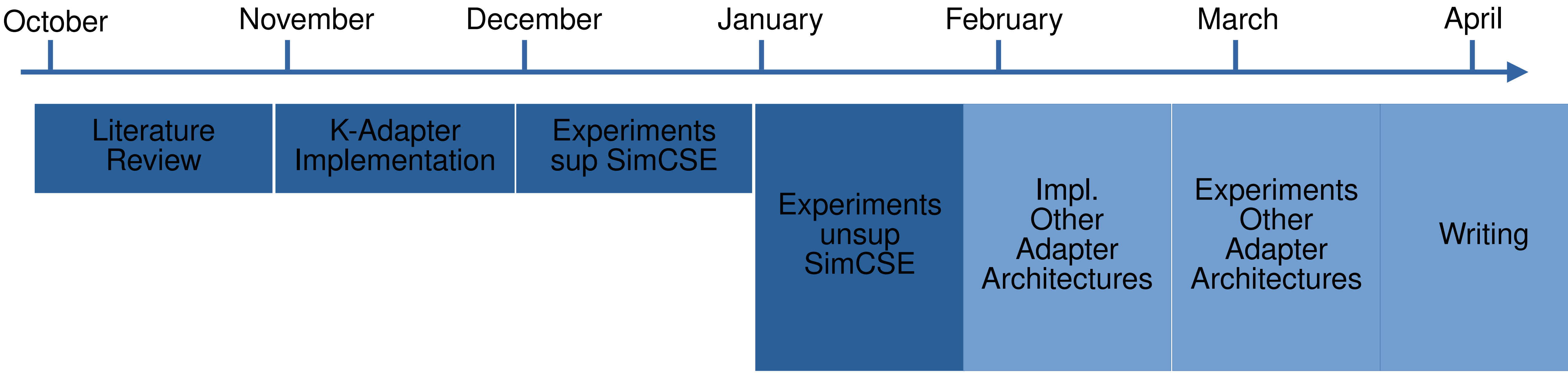
Model	STS12	STS13	STS14	STS15	STS16	STSBenchmark	SICKRelatedness	Avg.
Roberta	71.26	83.75	75.26	85.06	81.17	81.69	70.84	78.43
K-Adapter	73.37	84.89	76.21	87.24	83.17	81.79	72.63	79.90

Domain-specific Usage

RQ3: How to combine domain-specific Knowledge Adapters for the scholarly domain?

- Domain adaptation for training Sentence Embedding Models difficult
    - Usually no training data for specific domain available
- Train domain-specific adapters (MLM) and plug into generic STS-trained models

Timeline


October
November
December
January
February
March
April
Literature Review
K-Adapter Implementation
Experiments sup SimCSE
Experiments unsup SimCSE
Impl. Other Adapter Architectures
Experiments Other Adapter Architectures
Writing

Thank you for your attention

- Any questions?

References

- [1]: Kassner, Schuetze, 2020, Negated and misprimed probes for pretrained language models: Birds can talk, but cannot fly
- [2]: Goa et al. 2021, SimCSE: Simple Contrastive Learning of Sentence Embeddings
- [3]: Houlsby et al. 2019, Parameter-Efficient Transfer Learning for NLP