Towards Real-World Natural Language Processing

Heike Adel
Bosch Center for Artificial Intelligence

WiDS 2022

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Natural Language Processing
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- NLP = automatic processing of language

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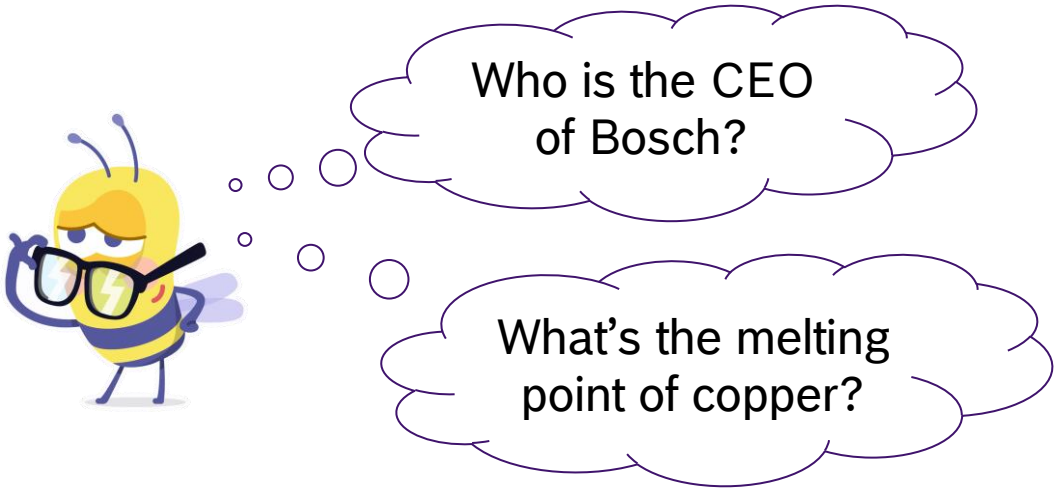

Heike Adel | 06.07.2022

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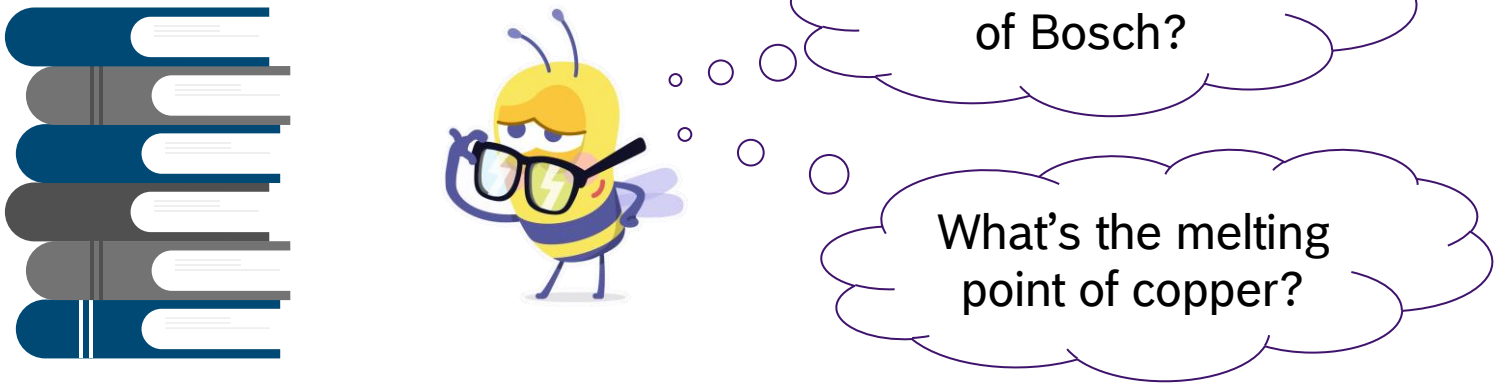

- Example NLP tasks relevant for answering those questions:
  - Information retrieval (keyword-based search)
  - Information extraction (concept and relation extraction)
  - Question answering

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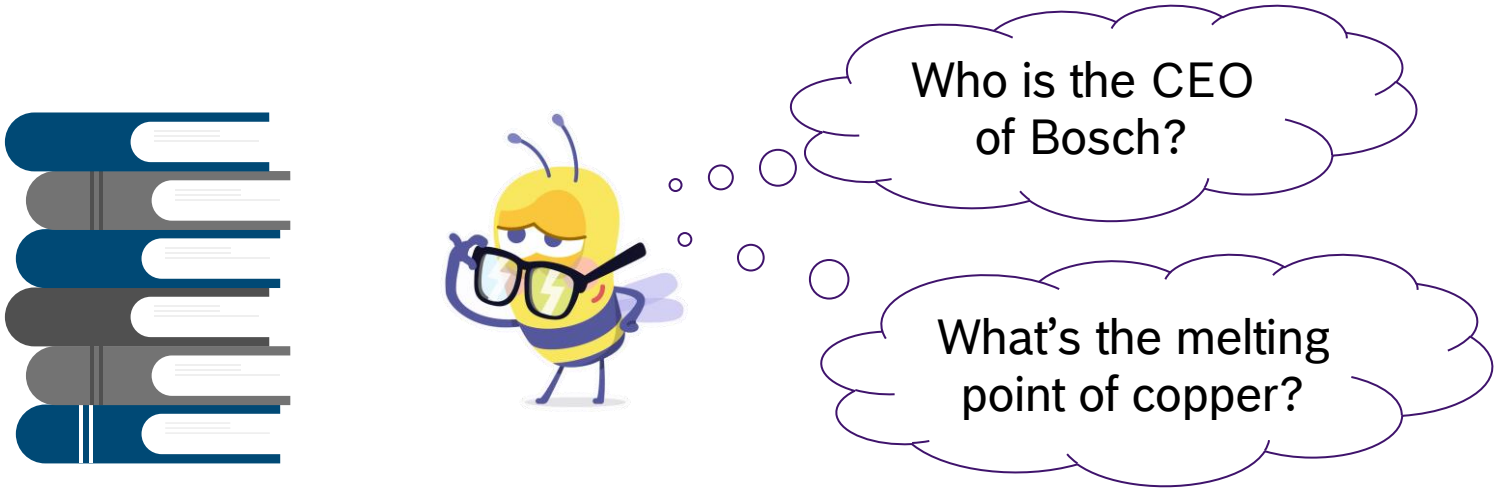

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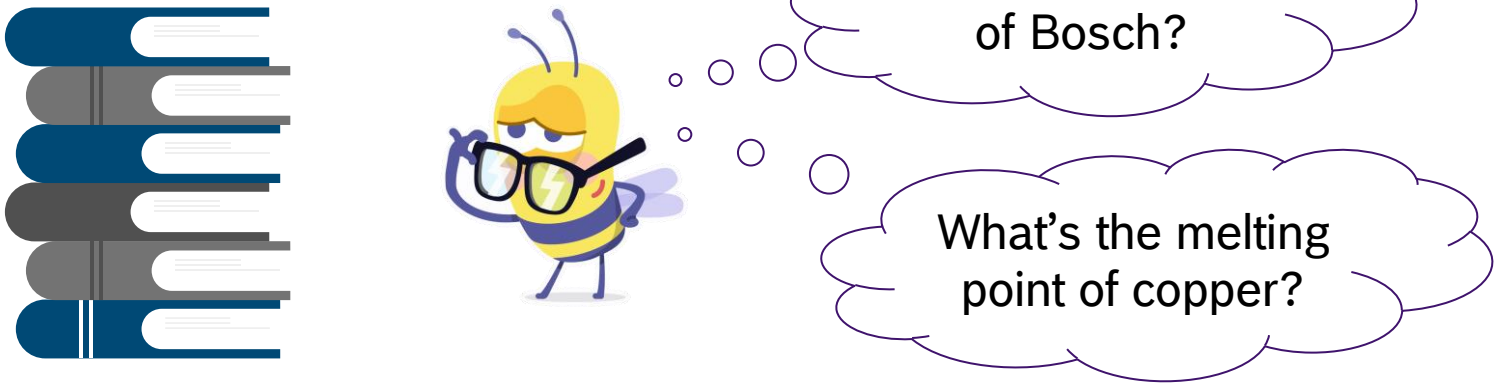

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focus of this talk

Natural Language Processing
Example Tasks

- **Information extraction** (concept and named entity recognition)
  - Goal: detection and typing of concepts and named entities
  - Example:

```
Ma founded Alibaba in Hangzhou.
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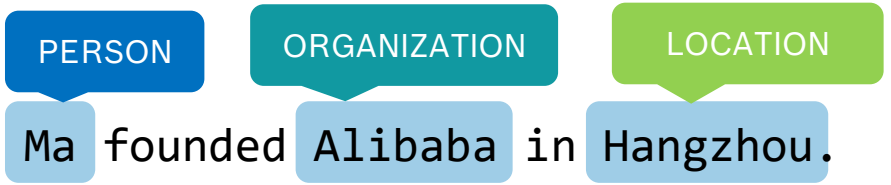

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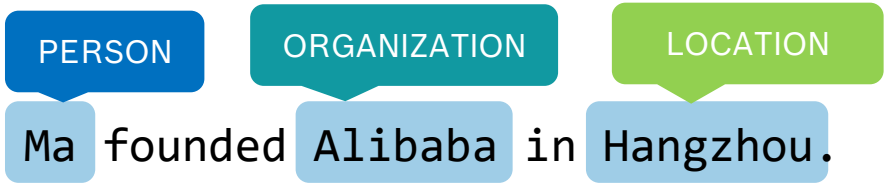
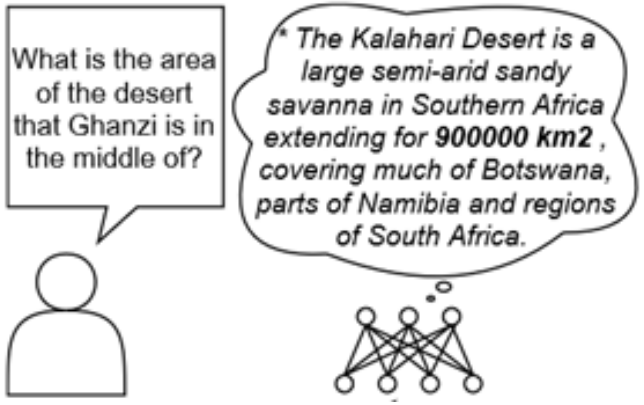
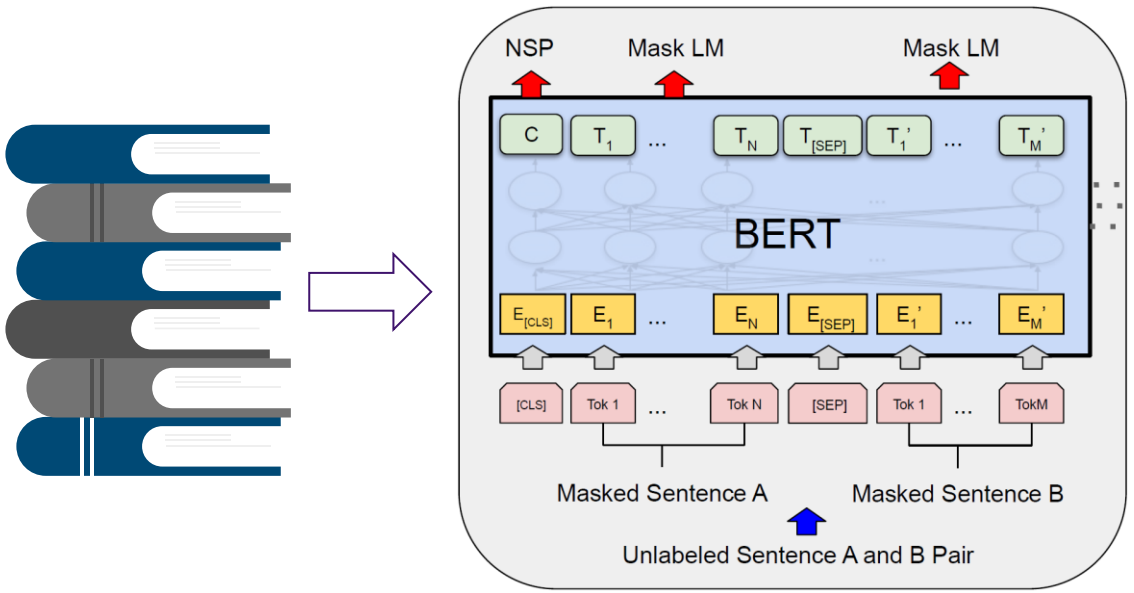


- **Question answering**
  - Goal: answer questions based on text document(s)
  - Variants: answer-span extraction vs. multiple-choice questions
  - Example:
    Given Wikipedia, find the answer to the question
    “What is the area of the desert that Ghanzi is in the middle of?”



Natural Language Processing
Current State of the Art



Step 1: pre-train (transformer-based) language model on large amounts of text

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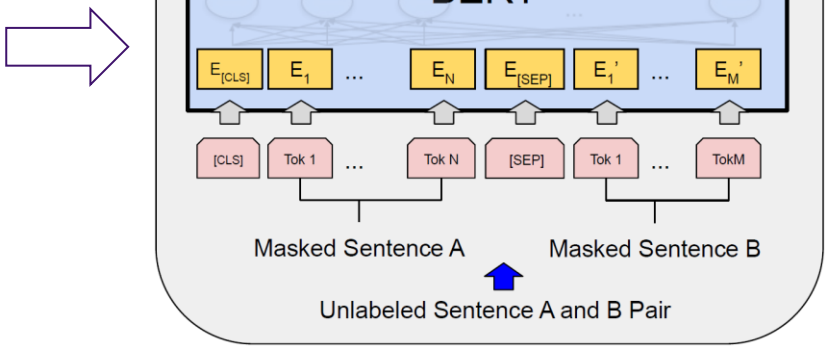

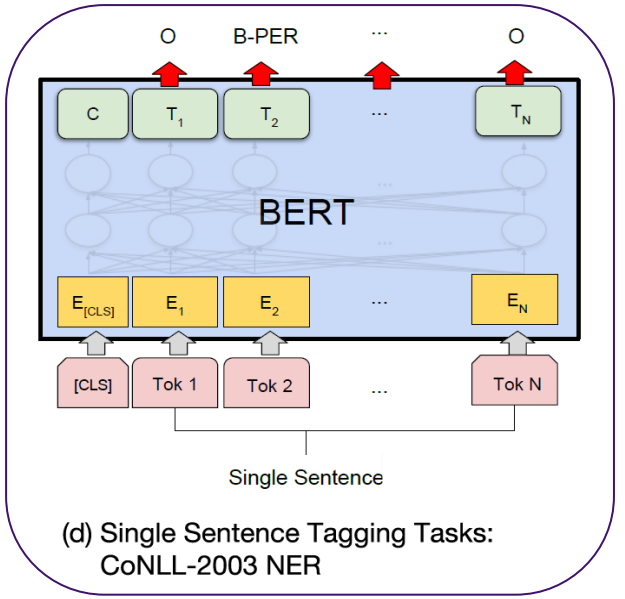

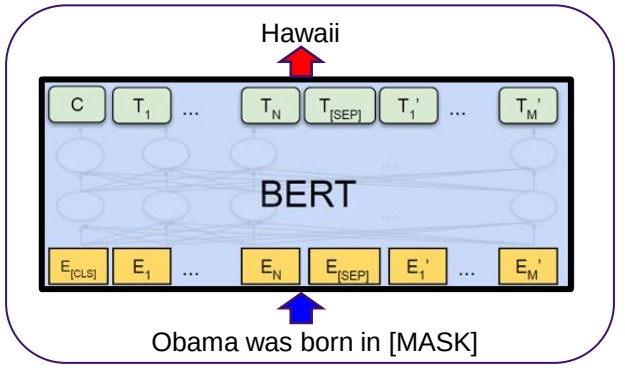

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or: use prompting

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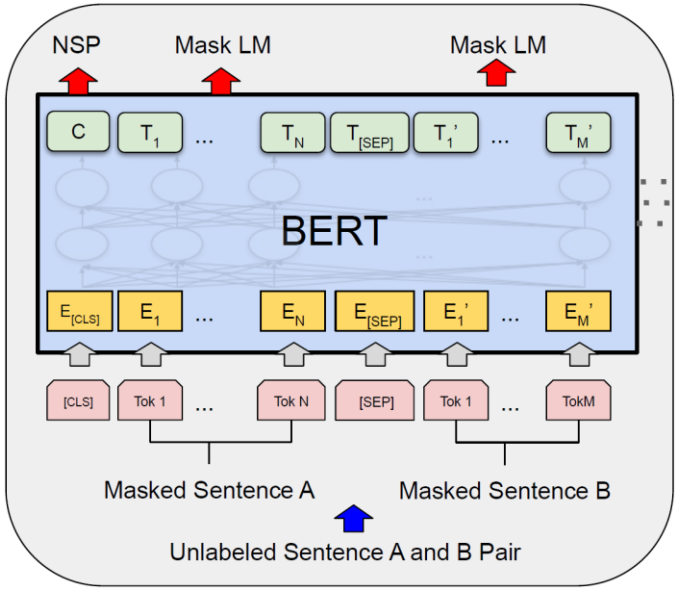

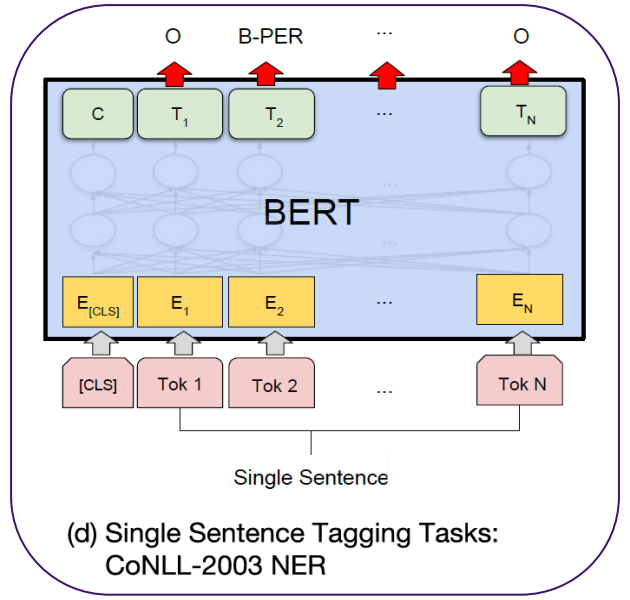

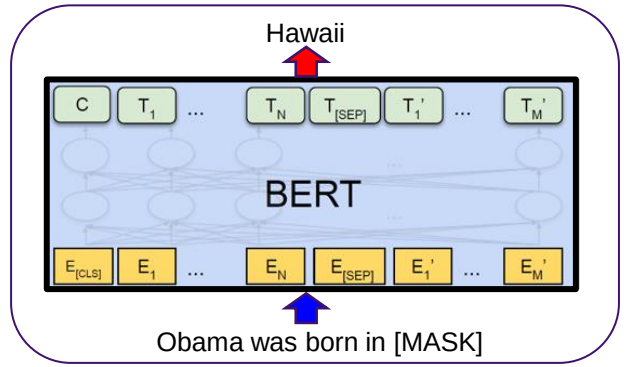

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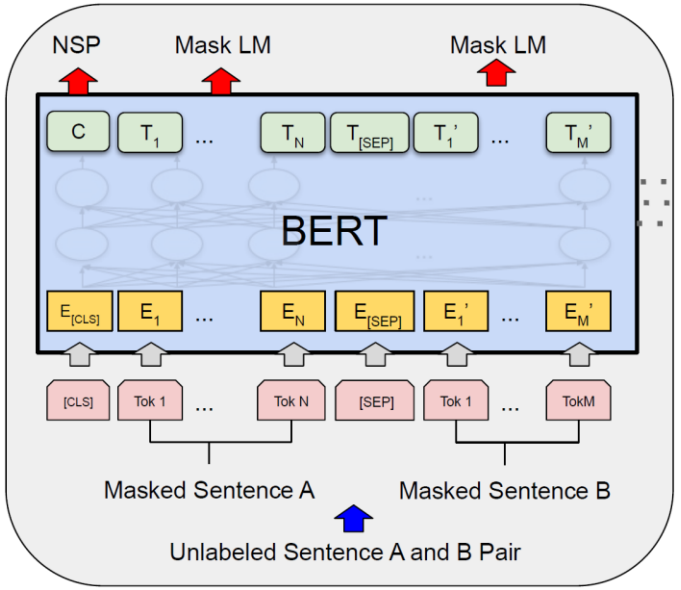

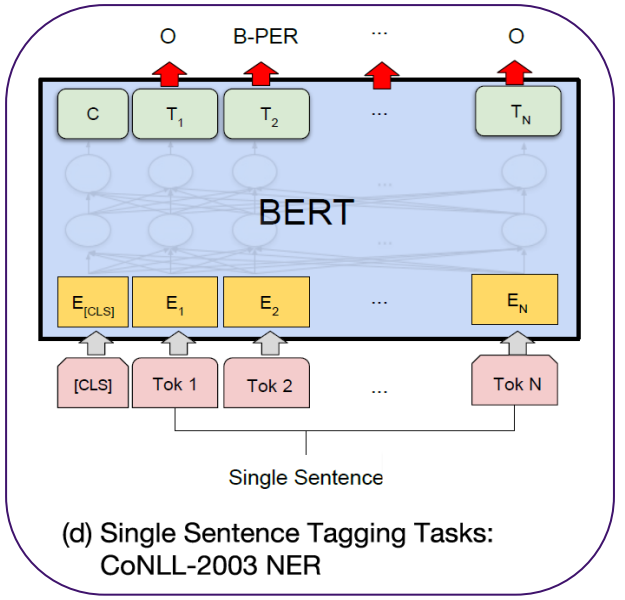

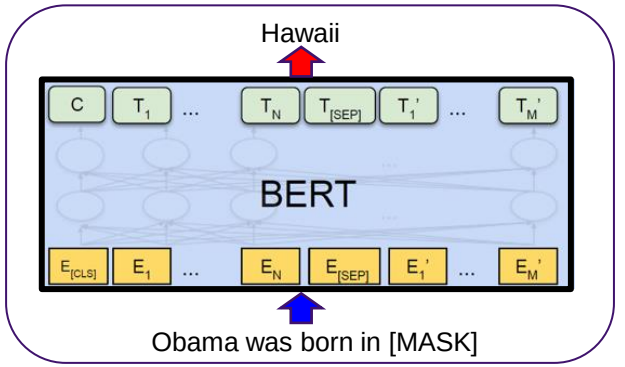

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- Problems (among others):
  - Focus on high-resource domains and languages
    - Not realistic: in reality we don't have labelled data for the tasks / domains / languages of interest
  - Black-box models
    - Explainability/interpretability required when deploying systems for real users

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This talk:

Low-Resource NLP

Explainable NLP

Low-Resource NLP
Motivation

- Current research focuses on high-resource domains and languages
  - Current deep-learning models are data hungry
  - Not realistic: In reality we don’t have labelled data for the tasks / domains / languages of interest
  - Possible directions: [Hedderich & Lange et al., NAACL 2021]
    - Creation of additional data (e.g., data augmentation, weak supervision)
    - Make use of unsupervised data (e.g., pre-trained language models)
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- Our approaches to cope with this challenge:
  - Meta-embeddings [Lange et al., EMNLP 2021]
  - Selection of Transfer Sources [Lange et al., EMNLP 2021]

Joint work with:

Lukas Lange, BCAI

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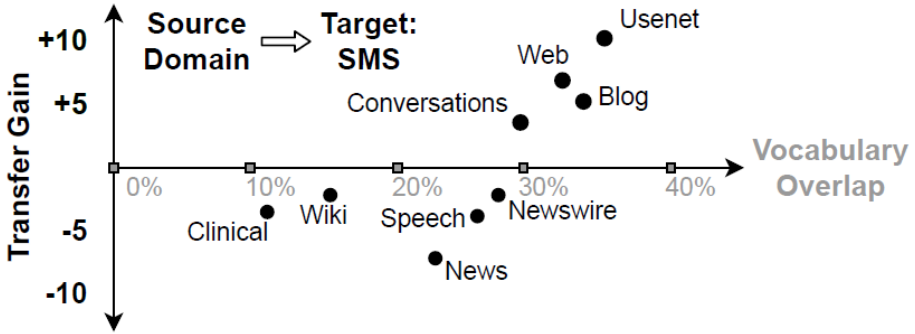
Transfer Learning: Selection of Transfer Sources

[Lange, Strötgen, Adel & Klakow, EMNLP 2021]

- Observation: Different performance gains can be expected for different transfer sources



- For some transfer sources, the performance might actually drop (negative transfer gain)
- How to avoid negative transfer gains?
- How to select the set of most promising sources?

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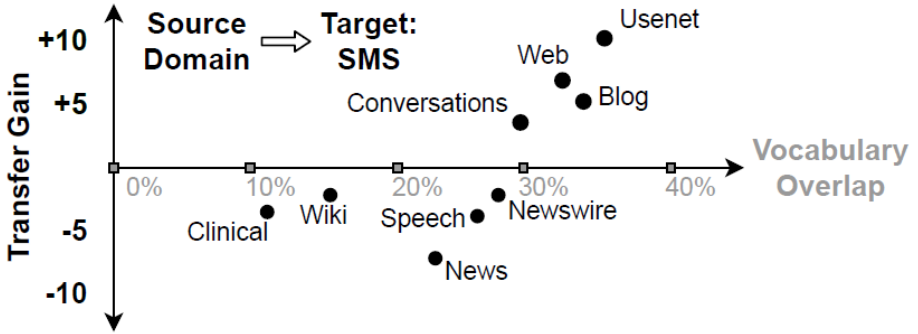

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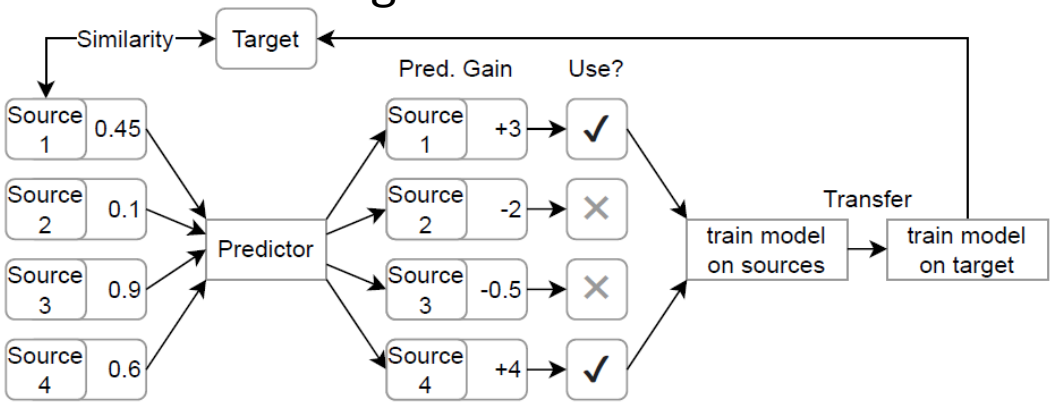
- Proposal: New similarity measure and new method for selecting set of sources:

Model similarity measure:

$$MoS(m_s, m_t) = |W - I|$$

$$\arg\min_W |W(f(m_s, t)) - f(m_t, t)|$$



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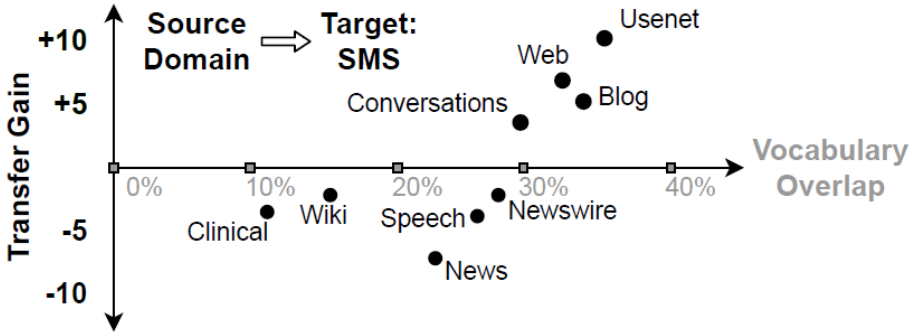

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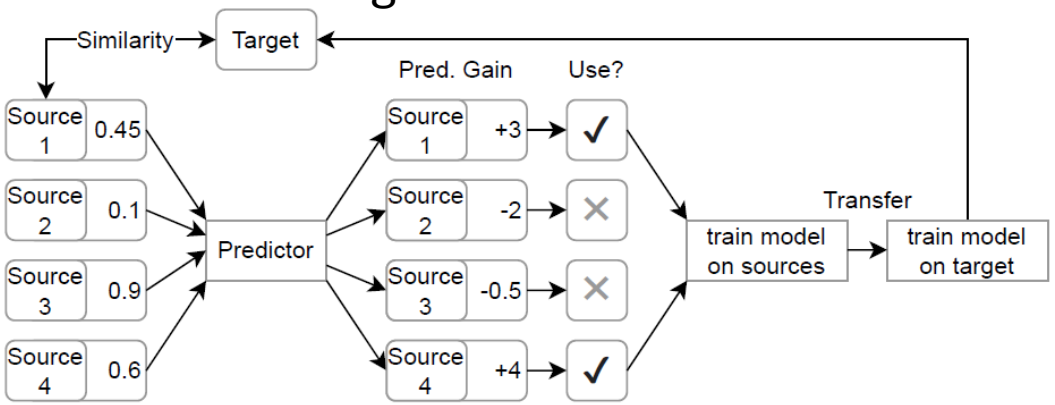

- **Take-home message:** Transfer learning is not successful by default: Carefully select the sources!

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- Current research focuses on black-box models
  - Explainability/interpretability required when deploying systems for real users
  - Another observation: Humans might not interpret model outputs or explanations as expected

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  Models → Evaluation → Perception
  - Coupling of prediction and explanation [Schuff et al., EMNLP 2020]
  - Evaluation scores [Schuff et al., EMNLP 2020]
  - Human interpretation of attribution scores [Schuff et al., FAccT 2022]

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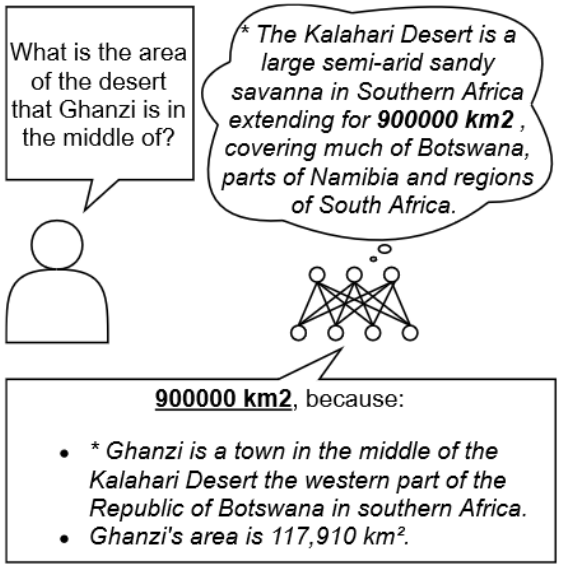

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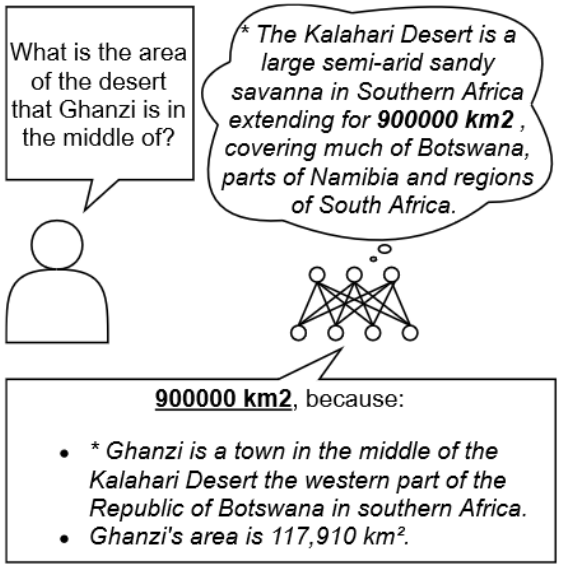

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- Proposal: Novel model architecture and loss function for ensuring coupling

Regulization term for loss:

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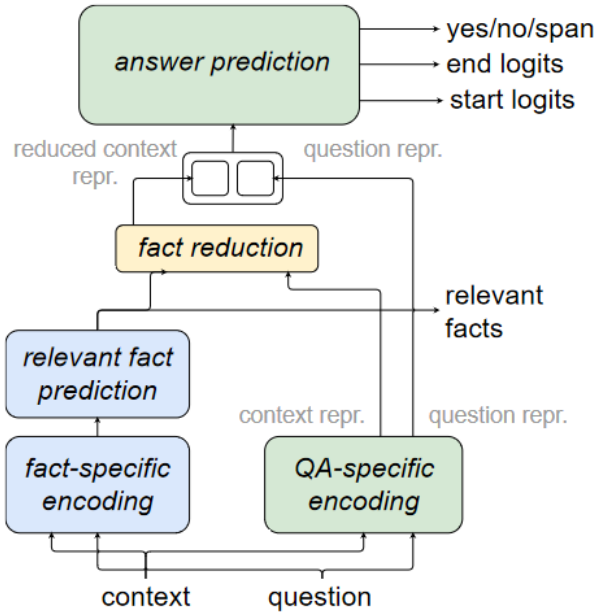
Select-and-forget architecture:



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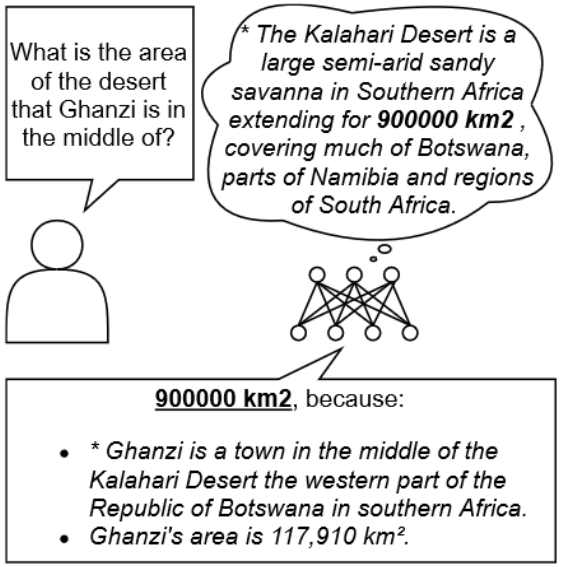

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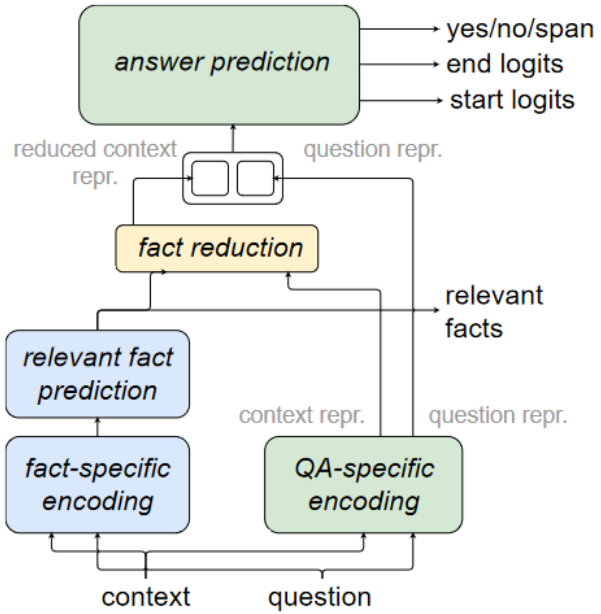
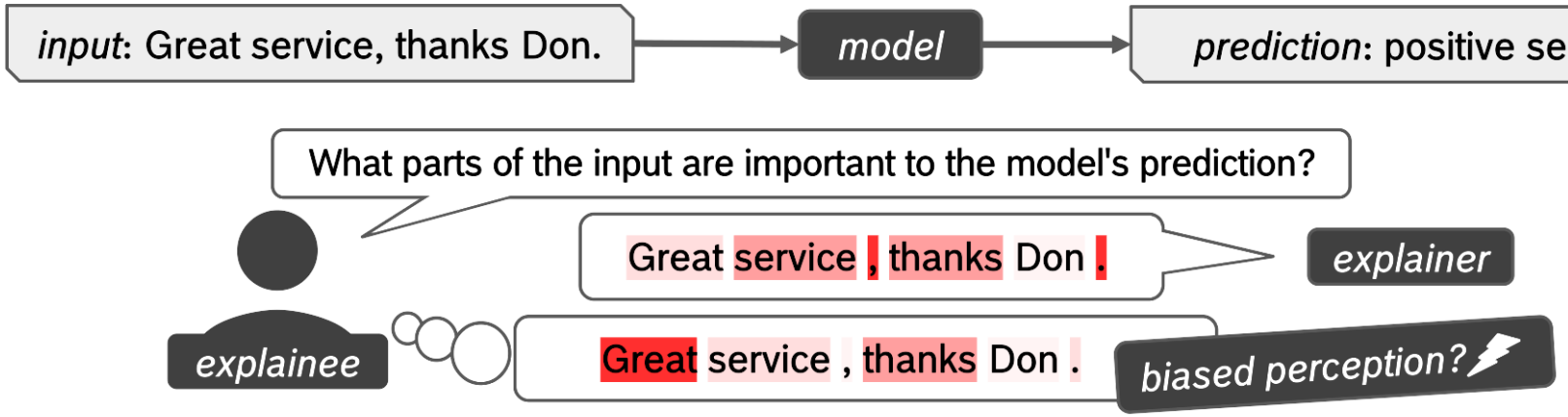


- Proposal: Novel model architecture and loss function for ensuring coupling
- **Take-home message:** Make sure that the explanations are coupled with the predictions of the model => otherwise they cannot be helpful for a user

Explainable NLP

Perception: Human Interpretation of Attribution Scores

[Schuff, Jacovi, Adel, Goldberg & Vu, FAccT 2022]



- Study: Which factors influence human interpretation of attribution scores?
  - Crowdsourcing user study (135 participants, >20k importance ratings, different languages / tasks / scores)
  - GAMM (Generalized Additive Mixed Model) for statistical analysis
  - Result: many biasing factors, e.g., word length, word position, capitalization, sentence length, saliency rank, …

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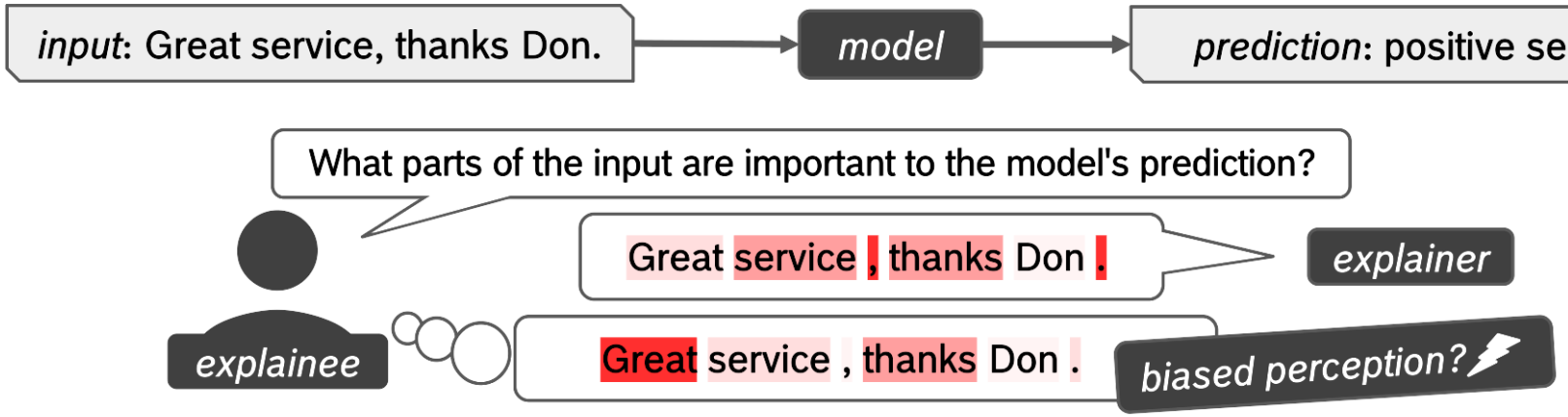

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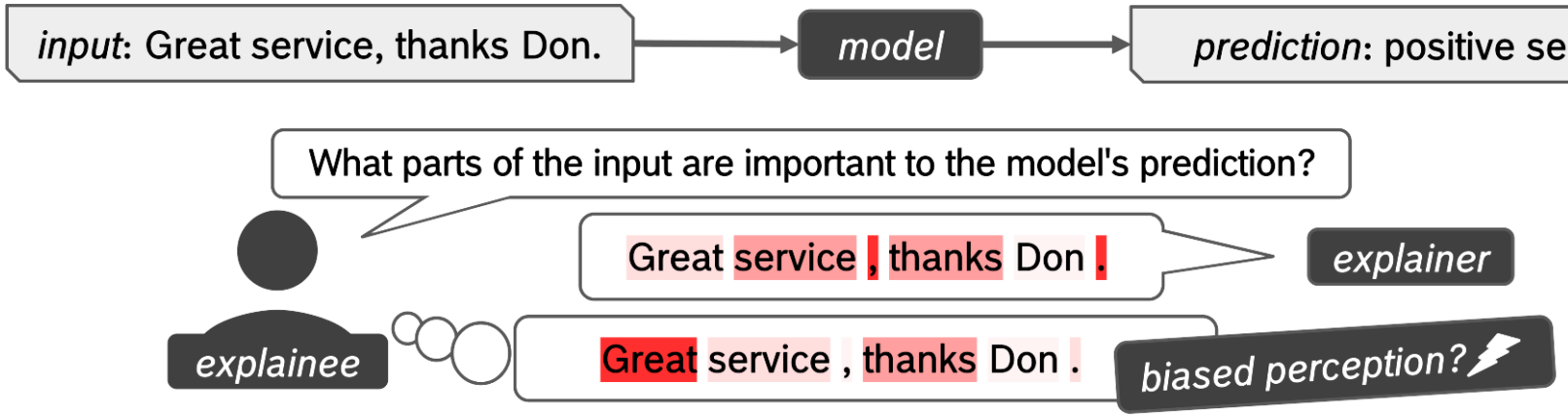

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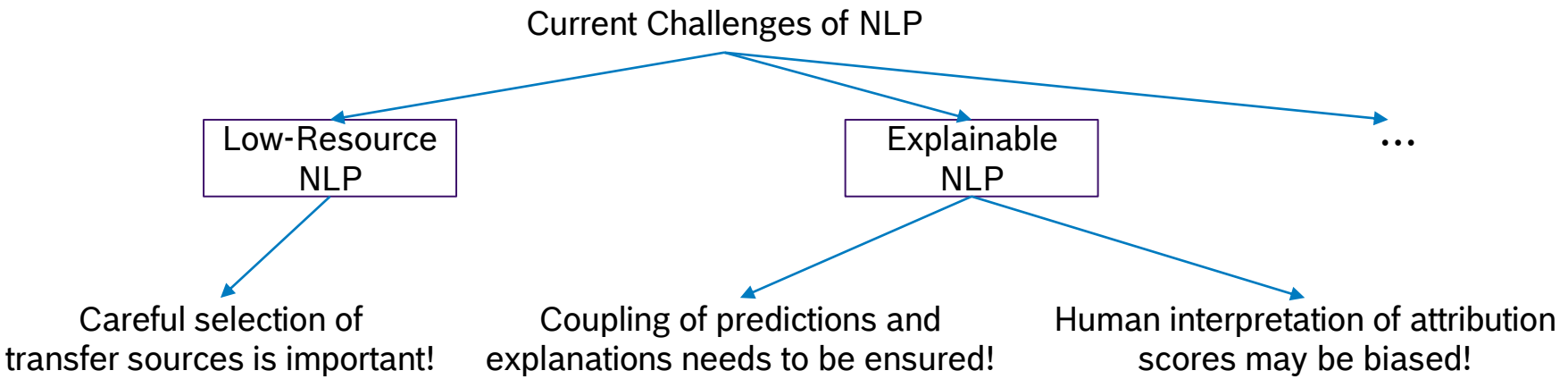
- Proposal to mitigate bias with using bar charts or adjusting salience scores
- **Take-home message**: Human perception of saliency explanations might be biased: Take this into account to ensure that explanations are actually helpful for users!

Conclusion
Summary and Outlook



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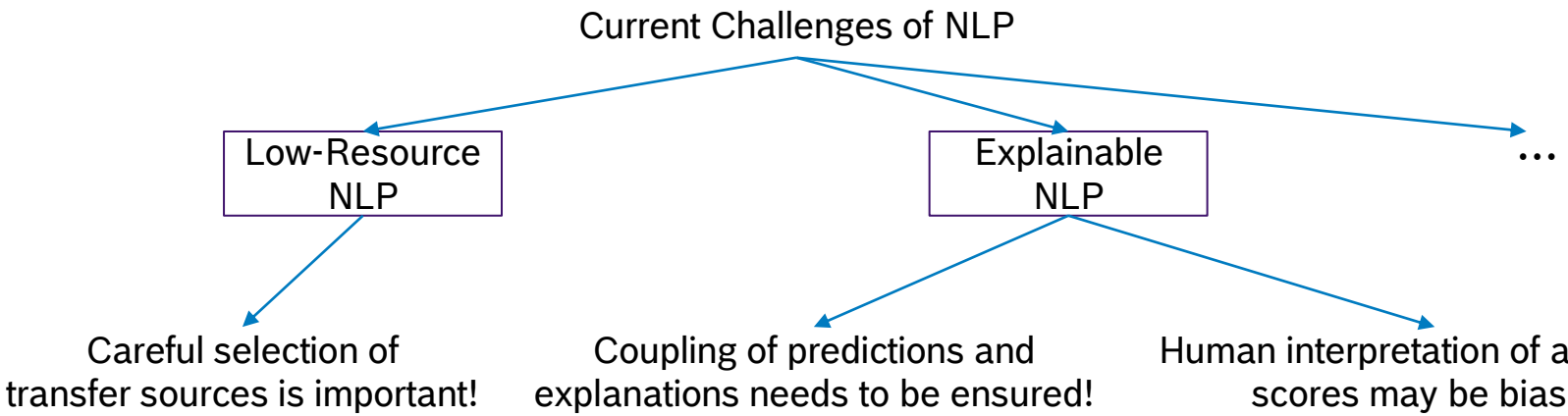

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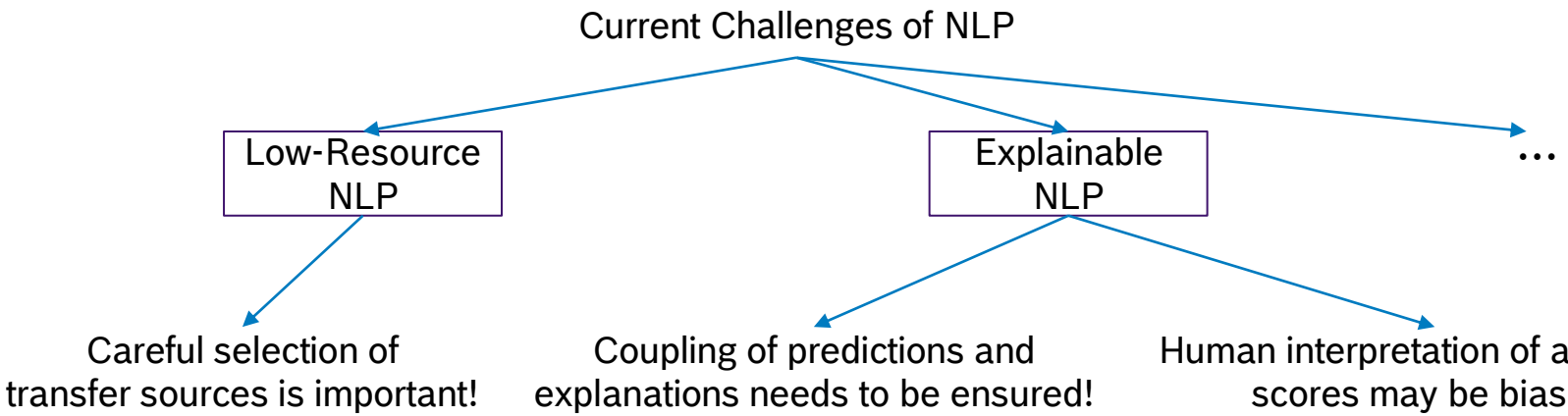

- This talk presented some steps towards natural language processing in real-world settings
- However, we still have a long road ahead of us
- Exemplary further directions:
  - How to effectively augment training data for NLP? Low-Resource NLP
  - How to analyze pre-trained language models and make best use of their “knowledge”? Explainable NLP

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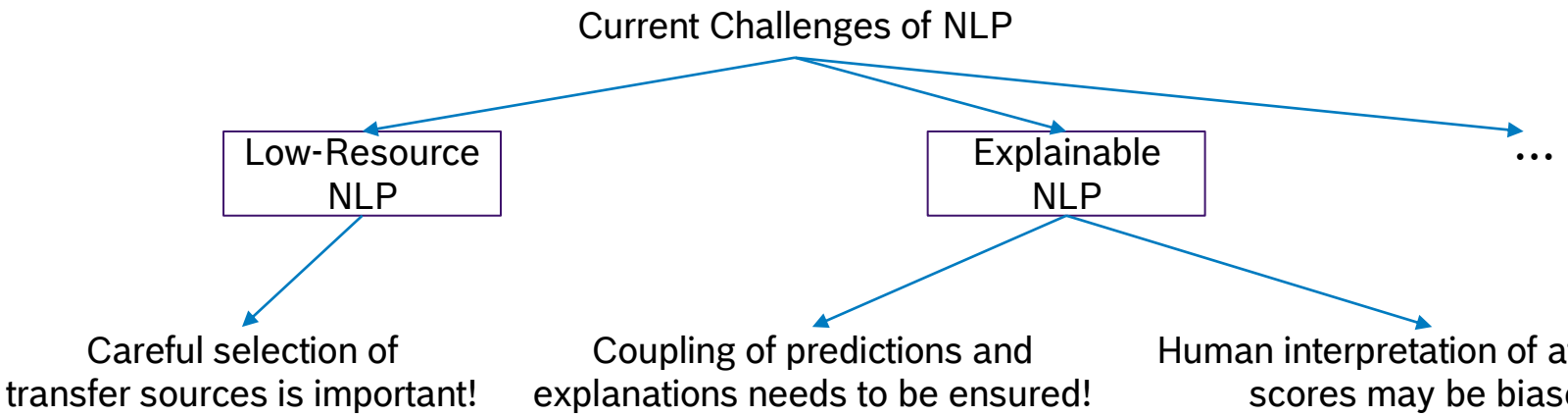
Thank you for your attention!



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- However, we still have a long road ahead of us
- Exemplary further directions:
  - How to effectively augment training data for NLP? Low-Resource NLP
  - How to analyze pre-trained language models and make best use of their “knowledge”? Explainable NLP