



# **NLP: Vorstellung Assignment**

KI Labor - Wintersemester 2022

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# Zeitplan

Datum	Thema	Inhalt	Präsenz
30. Sept	Allg.	Organisation, Teamfindung, Vorstellung CV	Ja
7. Okt.	Ausfall (DMA Techday)		
14. Okt.	CV	Q&A Sessions	Nein
21. Okt.	CV	Sprintwechsel, Vorstellung Assignment	Ja
28. Okt.	CV	Q&A Sessions	Nein
4. Nov.	CV / NLP	Abgabe CV, Vorstellung NLP	Ja
11. Nov.	NLP	Q&A Sessions	Nein
18. Nov.	NLP	Sprintwechsel, Vorstellung Assignment	Ja
25. Nov.	NLP	Q&A Sessions	Nein
2. Dez.	Ausfall (Winter Plenum)		
9. Dez.	NLP / RL	Abgabe NLP, Vorstellung RL	Ja
16. Dez.	RL	Q&A Sessions	Nein
23. Dez.	RL	Sprintwechsel, Vorstellung Assignment	Ja / Nein
13. Jan.	RL	Q&A Sessions	Nein
20. Jan.	RL	Abgabe RL, Abschluss Kl Labor	Ja



## Agenda

## > Besprechung Übungsaufgaben

- Word Embeddings Alice im Wunderland (Aufgabe 1)
- Sentiment Analyse f
  ür Twitter Posts (Aufgabe 2)

### Vorstellung Assignment

- Fine-Tuning bzw. Prompting mit Transformern



# Übungsaufgaben



# **Theorie**



## Scenario for this lecture

- > Task: Detecting sentiment on poem verses
- Dataset from Investigating Societal Biases in a Poetry Composition
   Systems; Emily Sheng, David Uthus; <u>2011.02686</u>
- Around 1100 crowd-sourced samples

Verse	Sentiment
that has a charmingly bourbon air.	Positive
ah, what a pang of aching sharp surprise	Negative
down in the west upon the ocean floor	No Impact (Neutral)



## **Examples in this lecture:**

- > Implement sentiment analysis for english poem verses
  - Fine-Tune a pre-trained model
  - Use prompting for a pre-trained model
- Compare different approaches and results
- Demo in Google Colab



# **Pre-Trained Language Models**



## **Pre-Trained Language Models (PLM)**

- Language Model (LM): Given a context, predict the next word:
  - the weather was  $[MASK] \Rightarrow [MASK] = (0.5 \text{ hot}, 0.3 \text{ cold}, ...)$
- Semi-supervised learning task (without labels)
  - Trained on very large datasets.
- **Transformer**-architecture scales up to trillions of parameters
- Large LM encode general knowledge features



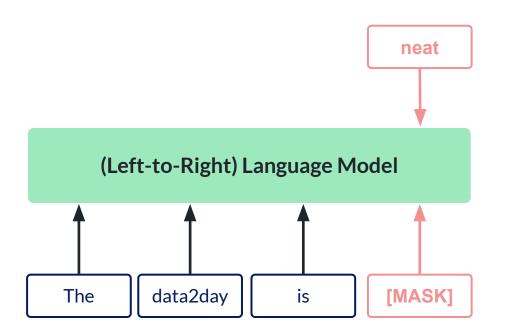


## Why "Pre-Trained"?

**Pre-Training Fine-Tuning or Prompting** Sentence Classification Language modeling Token Classification (NER) ••• Source task Target task(s)



## Left-to-Right language models



Predicts the next token given a sequence of tokens.

### **Models**

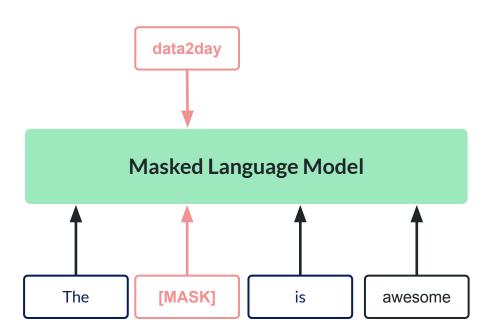
> GPT-2, GPT-3

### (Main) application

Text generation



## Masked Language Model (MLM)



Predicts a masked token in a sequence of tokens (cloze task).

### **Models**

> BERT

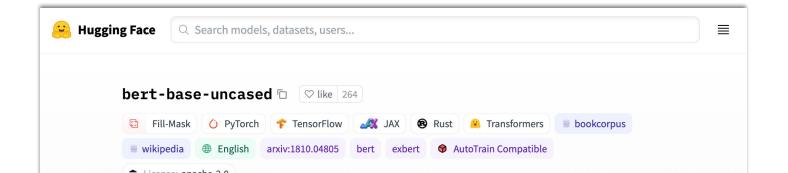
### (Main) application

Classification



## Our Scenario: Model and dataset

- Selecting the type of model
  - Masked language model for sentiment analysis
  - load <u>bert-base-uncased</u> from <u>huggingface transformers</u>
- > Prepare the dataset
  - Load the poem sentiment dataset with <u>datasets</u>
  - Tokenization





# **Fine-Tuning**

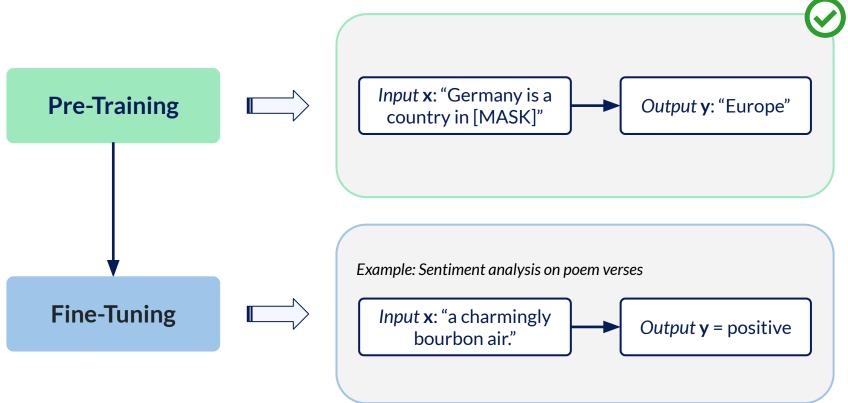


## **Pre-Training and Fine-Tuning**

**Pre-Training** Fine-Tuning or Prompting **Sentence Classification** Language modeling Token Classification (NER) Source task Target task(s)

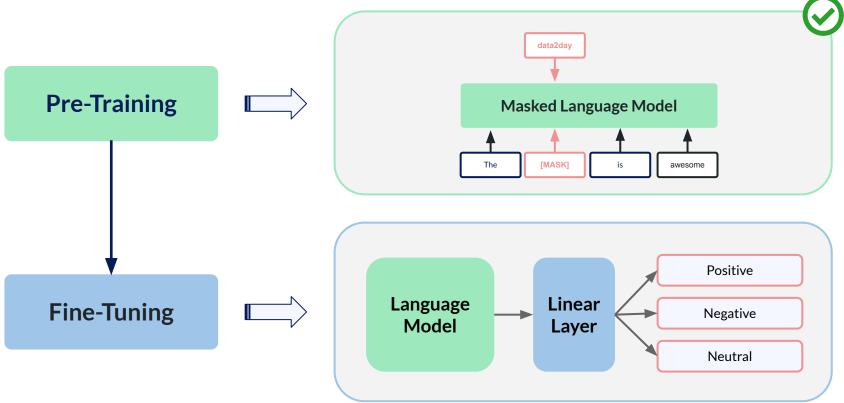


## **Fine-Tuning: Sentiment Analysis**





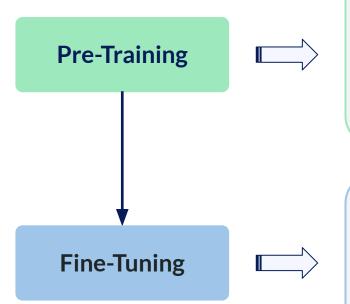
## **Pre-Training and Fine-Tuning**





## Our Scenario: Fine-Tuning the model





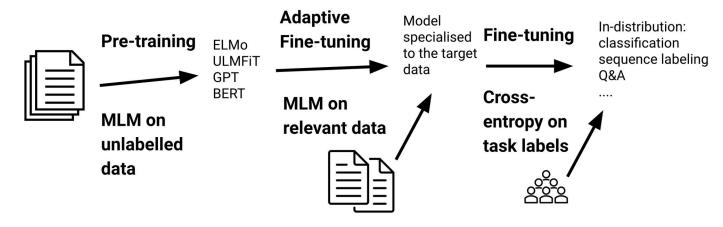
Download bert-base-uncased model from huggingface model hub.

Fine-tune bert-base-uncased for text classification and the sentiment task.



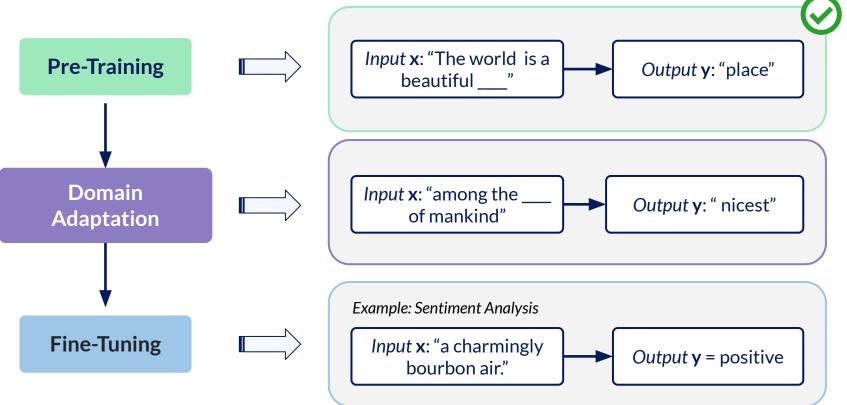
## **Adaptive Fine-Tuning**

- Additional step to continue the pre-training on different data
- Can be domain-, task- or language-specific.
- > Improves performance while losing the generalization capabilities.





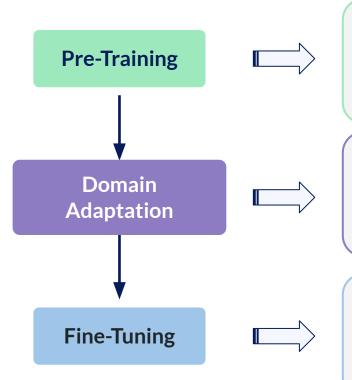
## **Adaptive Fine-Tuning: Domain Adaptation**





## **Our scenario: Domain Adaptation**





Download bert-base-uncased from huggingface model hub.

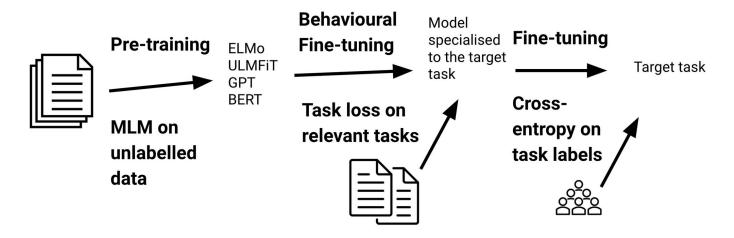
Continue Pre-training (!) with public available poem dataset (not the poem sentiment used for fine-tuning!)

Fine-tune adapted-1m on sentiment task with sentiment poem dataset (as before).



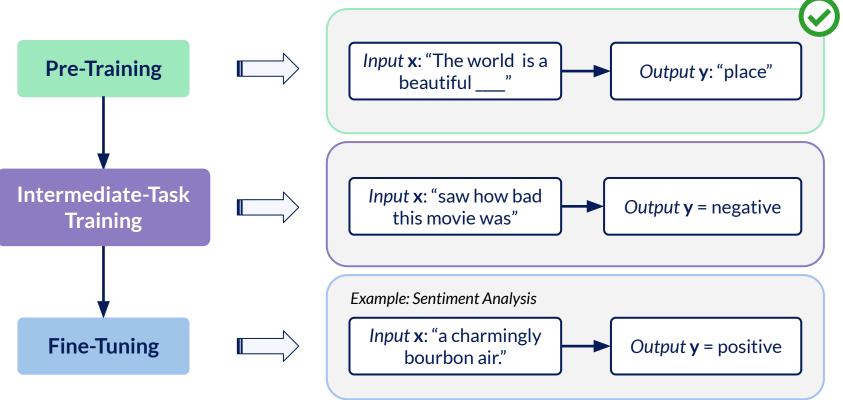
## **Behavioural Fine-Tuning**

- > Additional step to teach the model task-specific behaviour
- Intermediate-task training: Supervised learning of a related task (for instance for named entities)





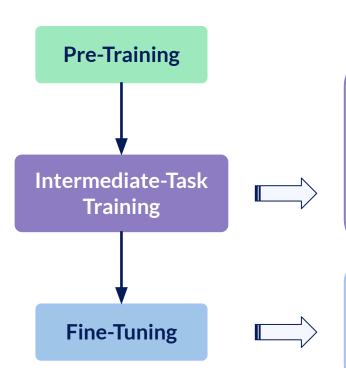
## Intermediate-task training





## Our scenario: Intermediate-task training





Use model bert-base-uncased-sst2

- provided by the community (!)
- trained on SST2 and GLUE dataset

Fine-tune bert-base-uncased-sst2 on sentiment task with poem dataset.



## **Summary: Fine-Tuning**

- > Fine-Tuning has become fast and straight-forward
- Domain adaptation can help to transfer to a different domain / language
- > Intermediate task-training can teach task-specific knowledge.



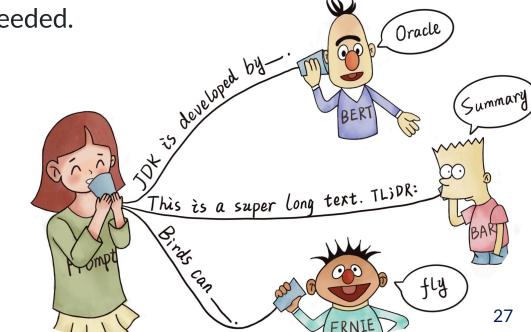
# **Prompting**



## **Prompting Overview**

Define a **prompt** to formulate the original task as language modeling problem.

- No architectural changes needed.
- Popularized by GPT-3
- Mainly possible with large models





# Zero-/Few-Shot-Learning

### Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

### Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
Translate English to French: 

sea otter => loutre de mer 

peppermint => menthe poivrée

plush girafe => girafe peluche

cheese => 

prompt
```

Beispiele: <a href="https://beta.openai.com/examples">https://beta.openai.com/examples</a>



## **Chain-of-Thought Prompting**

### Standard Prompting

#### Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

#### **Model Output**

A: The answer is 27.



### Chain of Thought Prompting

#### Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

#### **Model Output**

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9.

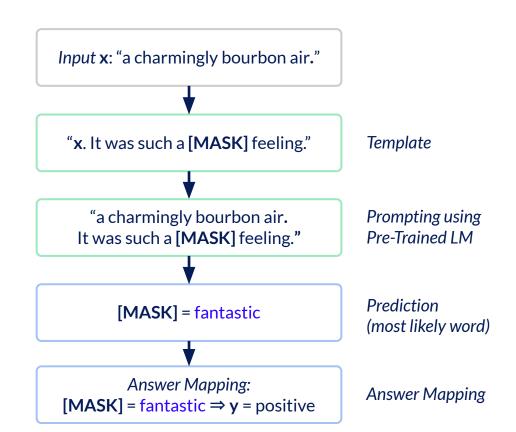


https://ai.googleblog.com/2022/05/language-maodels-perform-reasoning-via.html

## **Aspects of Prompting**

**Prompt Design** 

Answer Engineering (Verbalizer)

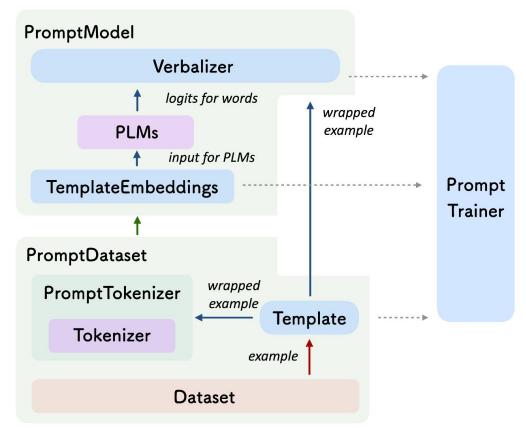




## **OpenPrompt**

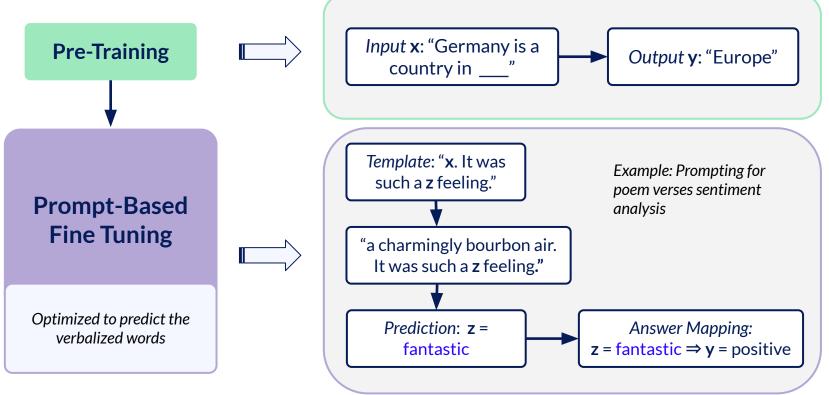


- OS Framework for Prompt Learning
- Simplifies usage and generation of prompts
- Integrates huggingface transformers





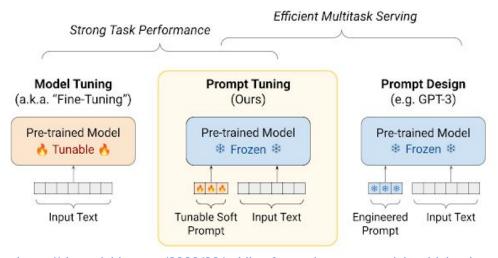
## **Prompt-Based Fine-Tuning**





## There is much more in prompting...

- › Automatic Prompt Search
- Soft Prompts instead of discrete prompts





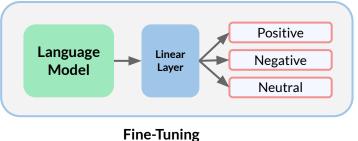
https://ai.googleblog.com/2022/02/guiding-frozen-language-models-with.html



## **Open-Ended Assignment Fine-Tuning and/or Promting**

## Anforderungen

- Wähle passende Transformer-Modelle (<a href="https://huggingface.co/">https://huggingface.co/</a>) und einen Datensatz zu einem NLP-Task (Translation, Text Generation, Classification, QA, ...)
- › Datensatz und Task erklären können
- > Wähle eine der folgenden Möglichkeiten auf den nächsten Slides







**Promting** 

## Möglichkeit 1

- > Fine-Tuning **und** Prompting
- > Beide initialen Ansätze ausprobieren
- › Beispiel: Fine-Tuning auf Dataset und Zero-Shot Prompting → Evaluation auf Test daten

**Fine-Tuning** 

- Fokus liegt auf Vergleich der beiden Ansätze
  - Welcher Ansatz funktioniert besser?
  - Wie verändern sich die Ergebnisse bei mehr Daten?
  - Vergleich der Ansätze auf großem vs. kleinem Sprachmodell?
  - ...





Fine-Tuning

**Prompting** 

## Möglichkeit 2

- > Fine-Tuning **oder** Prompting
  - Neben den initialen Ansätzen.
  - > Fine-Tuning: Ansätze wie Domain-Adaption und Intermediate-Task-Training
  - Prompting: Ansätze wie Automatic Prompt-Search, Prompt-Based Fine-Tuning,
     Parameter-Efficient Fine-Tuning
  - > Fokus liegt auf Vergleich der verschiedenen Ansätze
    - Bspw. Wie verändern sich die Ergebnisse, wenn Domain Adaptation bzw. Prompt-Based Fine-Tuning verwendet wird?
    - Welcher Ansatz liefert die besten Ergebnisse?



## Beispiel: Generierung von Book Reviews



https://www.bookreview.io/



- › Quellen zur Inspiration
  - https://beta.openai.com/examples
  - https://www.buildgpt3.com/
  - https://paperswithcode.com/methods/area/natural-language-processing
  - https://huggingface.co/models
- > Weitere Links
  - > Recent advances in Fine-Tuning: <a href="https://ruder.io/recent-advances-lm-fine-tuning">https://ruder.io/recent-advances-lm-fine-tuning</a>
  - Tutorial auf ACL22 zum Thema Prompting: <a href="https://github.com/allenai/acl2022-zerofewshot-tutorial/blob/main/acl2022-zerofewshot-tutorial.pdf">https://github.com/allenai/acl2022-zerofewshot-tutorial/blob/main/acl2022-zerofewshot-tutorial.pdf</a>



