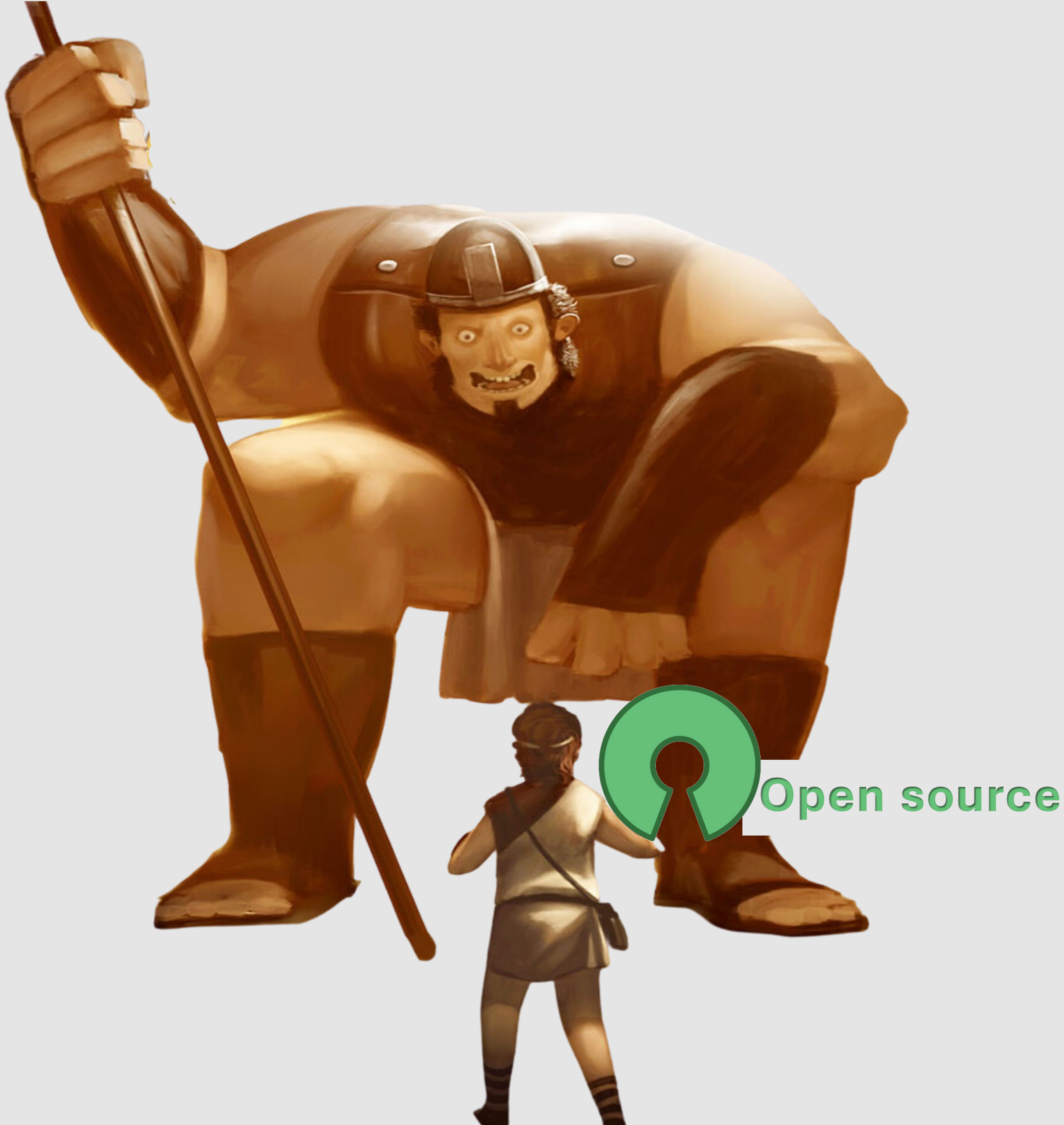
Hands-on Transformers:

Fine tune your own BERT and GPT

Moritz Laurer

22.08.2023



DAVID
AND
GOLIATH

ABOUT MYSELF

Moritz 👋

- Until 2018: Studied different social sciences
- Since 2018: programming for hobby projects & work
- 2018-2022: private sector (consultancy, think tank)
- Since 2021: PhD at Free University (VU) Amsterdam
  - Interest: Making supervised ML better with less training data
- Since 2022: Doing NLP consulting alongside PhD
- Open-source: models downloaded +20 million times

AGENDA

	10:00 – 10:10	**Introduction**
	10:10 – 10:35	The open-source NLP toolkit
	10:35 – 11:05	Transfer learning
	11:05 – 11:20	Inside Transformers
	11:20 – 12:00	Fine-tuning BERT
	12:00 – 12:20	*BREAK*
	12:20 – 12:35	Fine-tuning BERT-NLI
	12:35 – 13:20	Data-centric AI
LLM	13:20 – 13:40	Fine-tuning generative LLMs
+/-	13:40 – 14:00	LLM risks and opportunities

All materials on GitHub

https://github.com/MoritzLaurer/summer-school-transformers-2023/tree/main

Any initial questions?

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1

The open-source NLP toolkit

What are the software and hardware tools
for becoming “David”?

https://github.com/MoritzLaurer/summer-school-transformers-2023/tree/main

1_open_source_toolkit.ipynb

** Google account required*

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Why are (L)LMs powerful?

- Size
- Attention mechanism
- Layers
- Etc.

Transfer Learning

Transfer Learning

What:

Store ‘language knowledge’ and ‘task knowledge’ in the parameters of a model.

Why:

Learn new tasks faster & better.

2

Classical Algorithms
(e.g. Regression, SVM)

No prior
‘language knowledge’

No knowledge of semantic similarities between words like "*attack*", "*war*" and ”*tree*".

No prior
‘task knowledge’

No knowledge of tasks like "*Classify this text into ‘activist’ or ‘conservative’ rhetoric*".

2

Word Embeddings
(e.g. Word2Vec)

Provide '**language knowledge**':

- Represents "*attack*", "*war*" in similar static vectors

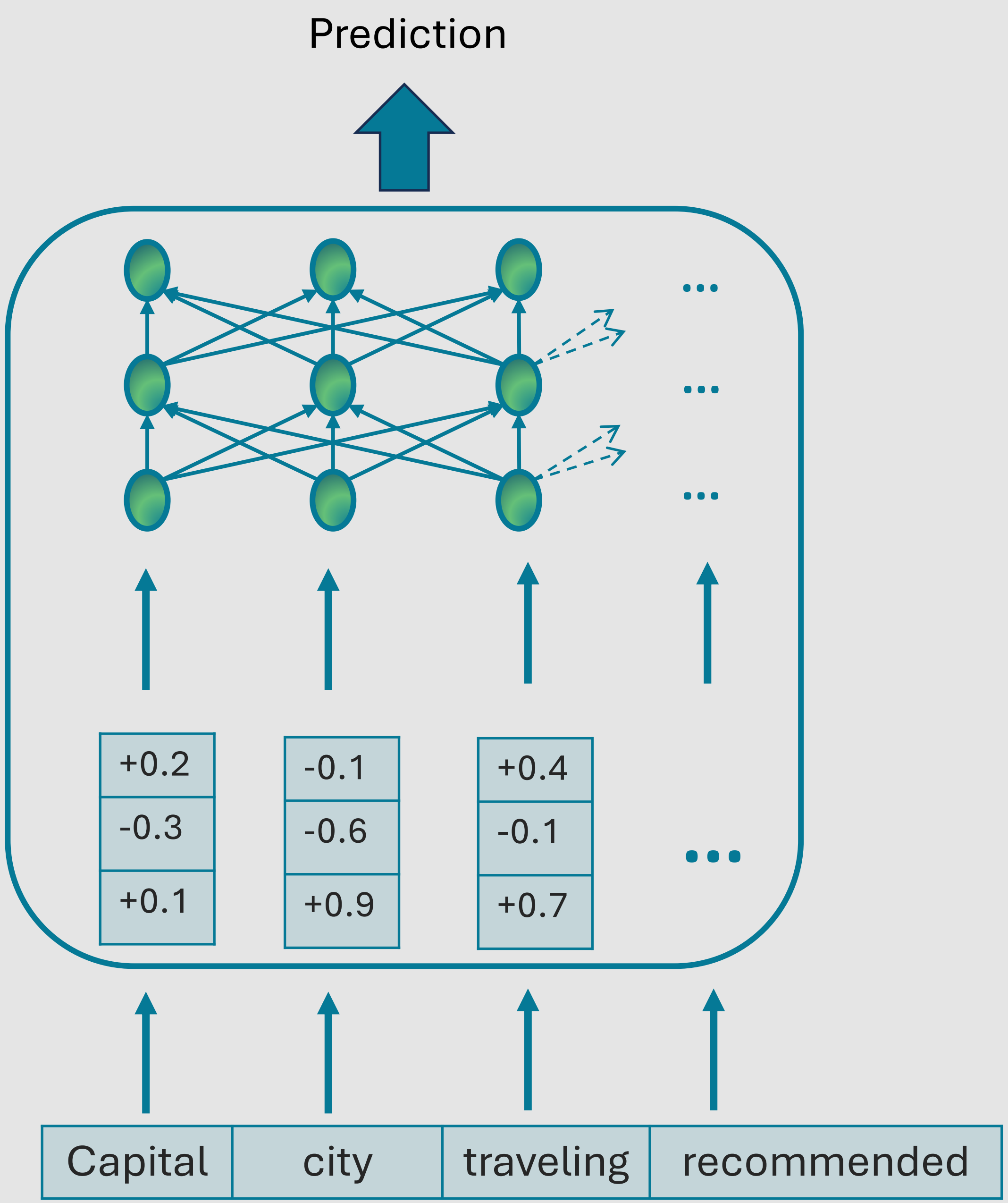
Attack ≈	0.1	0.8	...	-0.5	0.1
War ≈	0.2	0.8	...	-0.4	0.3
Tree ≈	0.7	-0.4	...	0.1	-0.7

Transformers
(e.g. BERT-base)

Prior **'language knowledge**’:

- Represents "*attack*", "*war*" in similar vectors
- Represents "*capital*" differently in context of "*city*" or “*investment*” or “*crime*”

2

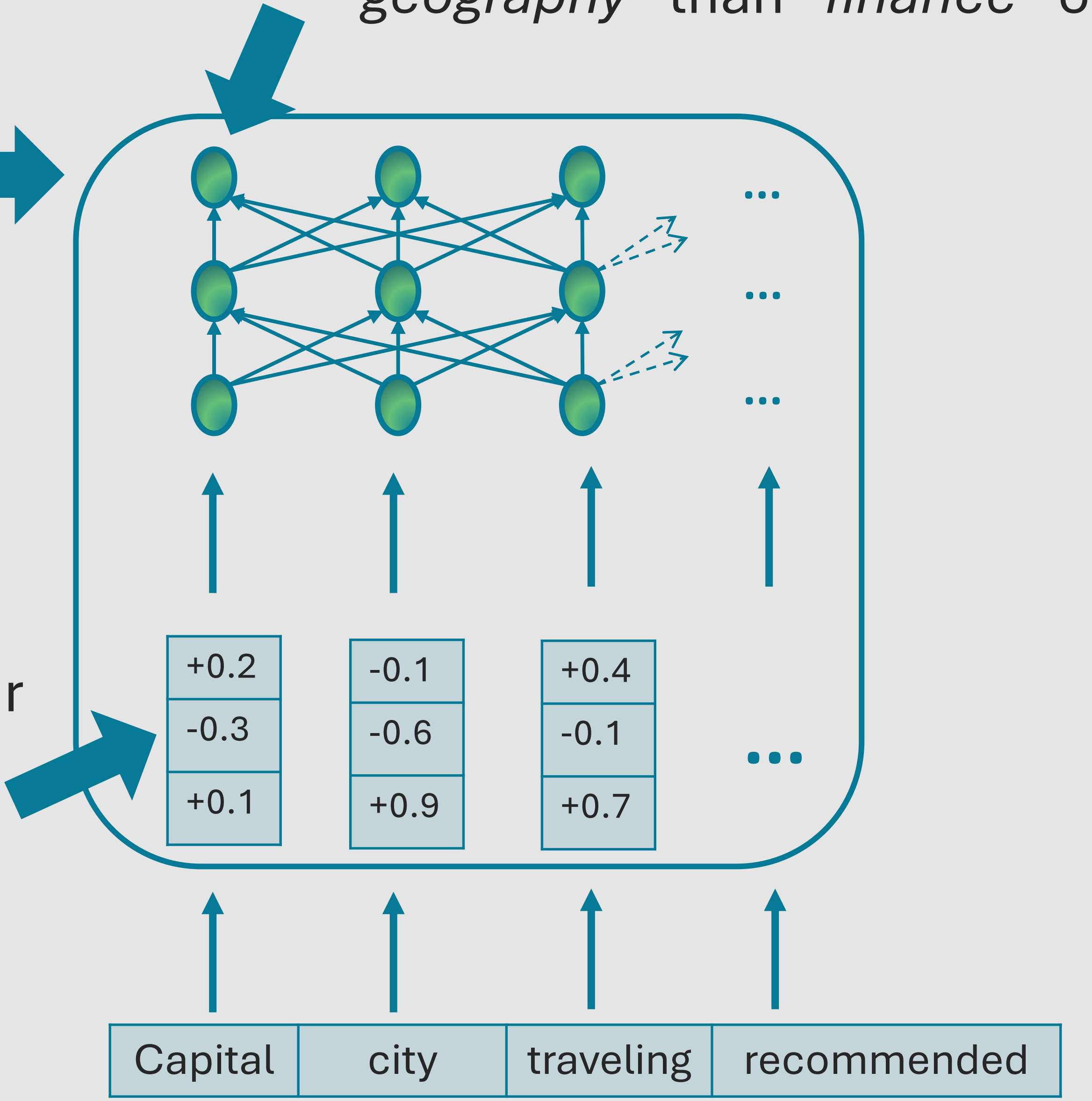


Prediction
...
...
...
+0.2
-0.3
+0.1
-0.1
-0.6
+0.9
+0.4
-0.1
+0.7
...
Capital
city
traveling
recommended

2

Word vector of “*capital*” now closer to “*geography*” than “*finance*” or “*crime*”

Last layer: Contextualised representation of input



Word vector of “*capital*” with similar distance to “*geography*” / “*finance*” / “*crime*”

2

Transformers
(e.g. BERT-base)

Prior **'language knowledge**’:

- Represents "*attack*", "*war*" in similar vectors
- Represents "*capital*" differently in context of "*city*" or “*investment*” or “*crime*”

Learned through **simple, self-supervised task**:

- Masked Language Modelling

2

How BERT acquires language knowledge

ORIGINAL TEXT

"Capital punishment, also known as the death penalty and formerly called judicial homicide, is ..."

MASKED TEXT

"Capital **[MASK]**, also known as the death **[MASK]** and formerly called **[MASK]** homicide, is ..."

The algorithm learns to predict the correct word behind the [MASK] token.

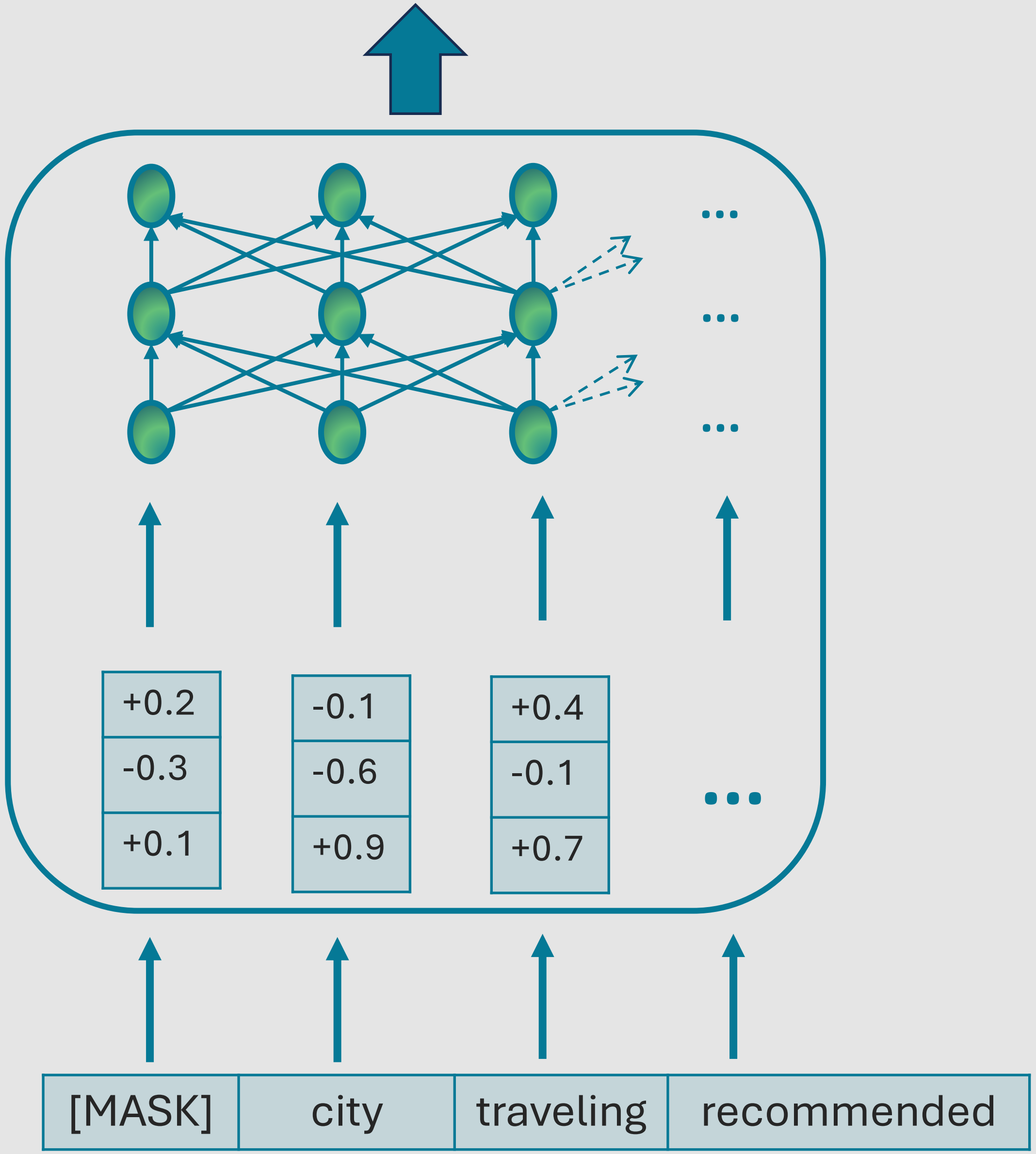
This creates general **'language knowledge'**

2

BERT-base

After millions of training iterations:

Many parameters (vectors), which are very good at predicting hidden words.



2

Disadvantages of BERT-base

‘Task knowledge’ from MLM is not useful:

- BERT-base only knows how to predict hidden words (MLM task)
- We are actually interested in other tasks like classification, summarization etc.
- BERT-base needs to learn new, useful tasks from scratch

2

Reusing more ‘prior knowledge’

Universal tasks

- Natural Language Inference (BERT-NLI)
- Next-word-prediction (GPT)

2

Natural Language Inference (NLI)

$\underbrace{\text{The EU betrayed its partners during the negotiations on Sunday.}}_{\textbf{context-sentence}}$ $\underbrace{\text{The EU is trustworthy.}}_{\textbf{hypothesis-sentence}}$

NLI Task

Is the **hypothesis** true/false/neutral, given the **context-sentence**?

→ NLI is the task of determining whether a given statement (hypothesis) can logically be inferred from another statement (context-sentence).

2

Natural Language Inference (NLI)

INPUT

CONTEXT-HYPOTHESIS PAIR

$\underbrace{\text{The EU betrayed its partners during the negotiations on Sunday.}}_{\textbf{context-sentence}}$ [SEP] $\underbrace{\text{The EU is trustworthy.}}_{\textbf{hypothesis-sentence}}$

OUTPUT

PROBABILITY OF 3 UNIVERSAL CLASSES

True: 0.01 **False: 0.83** Neutral: 0.26

2

Universal Task & Label Verbalisation

Example task:

Identifying texts that indicate that the economy is performing well / badly

Task reformulated for NLI:

NLI-input	*NLI-Output*
{context-sentence from news} [SEP] {hypothesis-sentence verbalising label}	Most "True" label

"The Rubel plummeted amidst a surge of investors withdrawing from Russia [SEP] The economy is performing badly"	**0,61 True** 0,13 False 0,26 Neutral
"The Rubel plummeted amidst a surge of investors withdrawing from Russia [SEP] The economy is performing well"	0,19 True 0,38 False 0,43 Neutral

2

Universal Task & Label Verbalisation

NLI-input	***NLI-Output***
{context-sentence from news} [SEP] {hypothesis-sentence verbalising label}	Most "True" label

“The politicians were bribed by lobbyists. [SEP] It is about corruption.”	**0,61**
“The politicians were bribed by lobbyists. [SEP] It is about peace.”	0,01
“The politicians were bribed by lobbyists. [SEP] It is about free market.”	0,06
“The politicians were bribed by lobbyists. [SEP] It is about equality.”	0,04
...	...

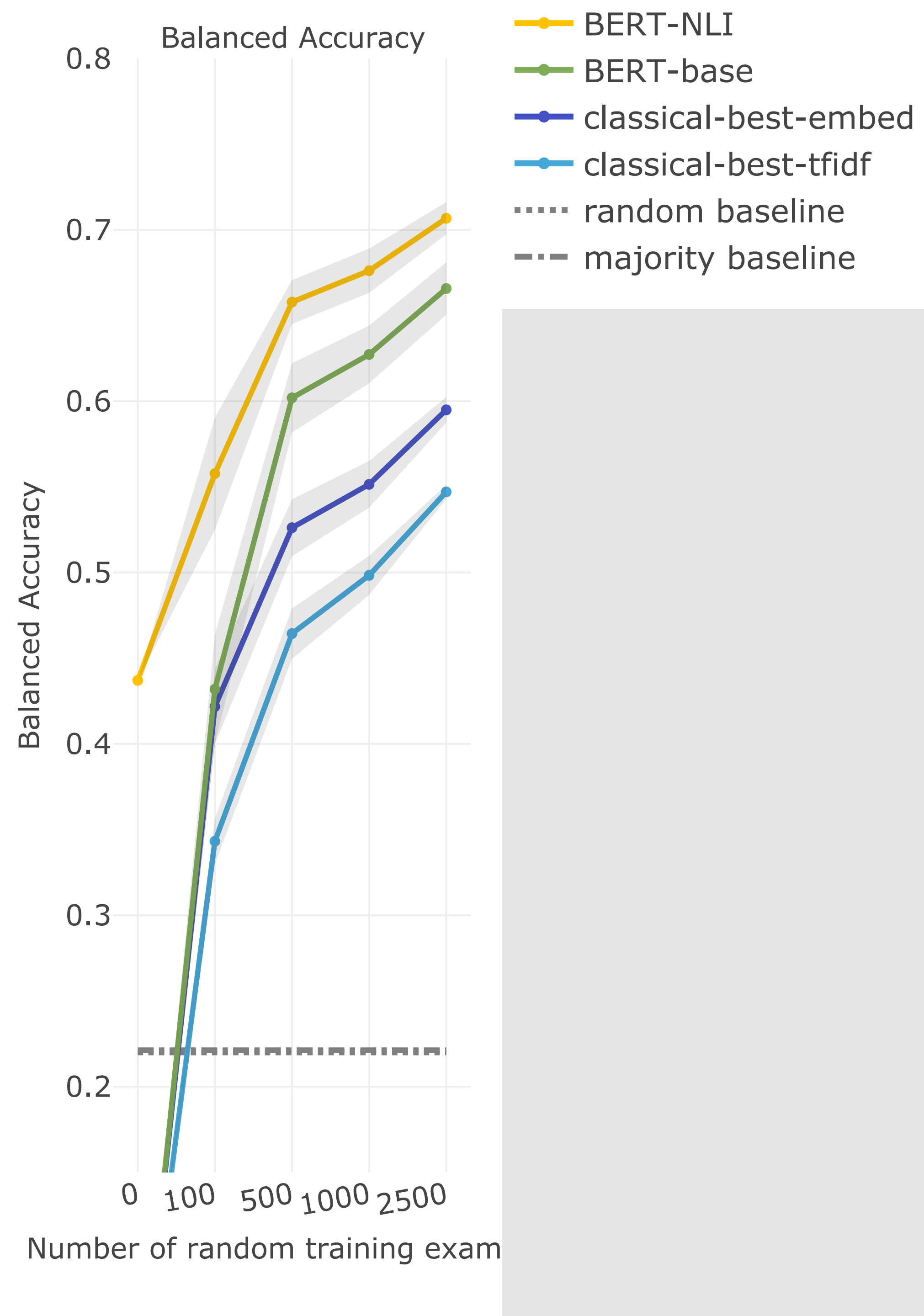
NLI: Data-Rich Task

NLI is a data rich task

- Many NLI datasets with over 1 million annotated sentence pairs from different domains exist.

- Examples: *SNLI (570k examples, Bowman et al. 2015), MultiNLI (433k, Williams et al. 2018), ANLI (162k, Nie et al. 2020)*

→ **Helps address the issue of data scarcity**



Average performance across eight tasks vs. training data size

[Laurer et. al 2023]

2

Limitations of NLI

- Usefulness decreases with training data size. If there is enough data to learn the new task (> 1000 texts), BERT-base is better.
- BERT-NLI can only do classification tasks.
- No summarization, translation, information extraction ...

2

A more universal task

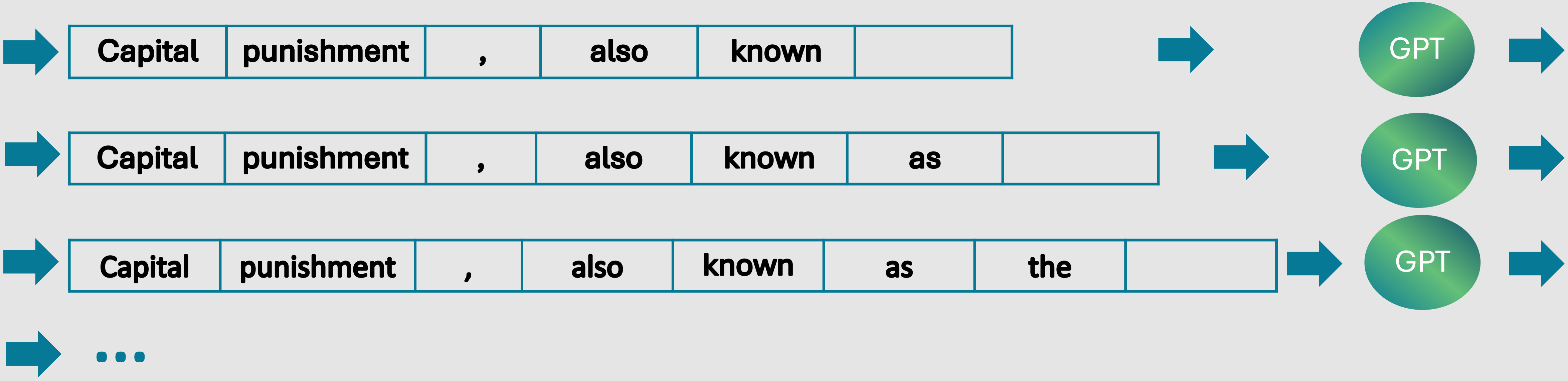
Next-token-prediction

- Main pre-training task of GPT models
- Is a self-supervised task (no manual annotations)

Next-token-prediction task

Original text:

“Capital punishment, also known as the death penalty and formerly called judicial homicide, is …”



Universal task

Sentiment classification

[long text ...]	Is	this	text	positive	or
negative	?				

GPT

[long text ...]	Is	this	text	positive	or
negative	?	**positive**			

2

Universal task

Information extraction

[long text ...]	Extract	all	countries	from	the
text	:				

GPT

[long text ...]	Extract	all	countries	from	the
text	:	**Germany**			

GPT

[long text ...]	Extract	all	countries	from	the
text	:	**Germany**	,		

GPT

...

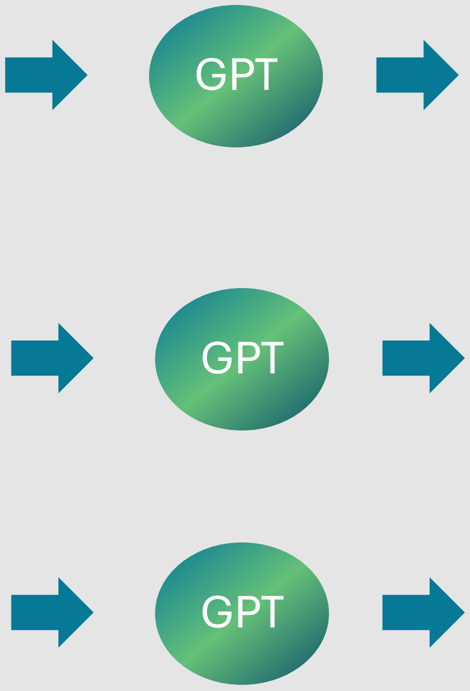
Universal task

Summarisation

[long text ...]	A	summary	of	the	preceding
text	:				

[long text ...]	A	summary	of	the	preceding
text	:	**The**			

[long text ...]	A	summary	of	the	preceding
text	:	**The**	**main**		



...

2

Reflect and Q&A

- Q1: What is the difference between word embeddings and BERT?
- Q2: What are universal tasks and why are they useful?
- Q3: In your own words, try to define transfer learning.

Write your responses on a piece of paper / notebook.
Ask any questions about the slides in the chat.

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Inside Transformers

Demo of main components of
Transformers with Hugging Face

https://github.com/MoritzLaurer/summer-school-transformers-2023/tree/main

2_inside_transformers.ipynb

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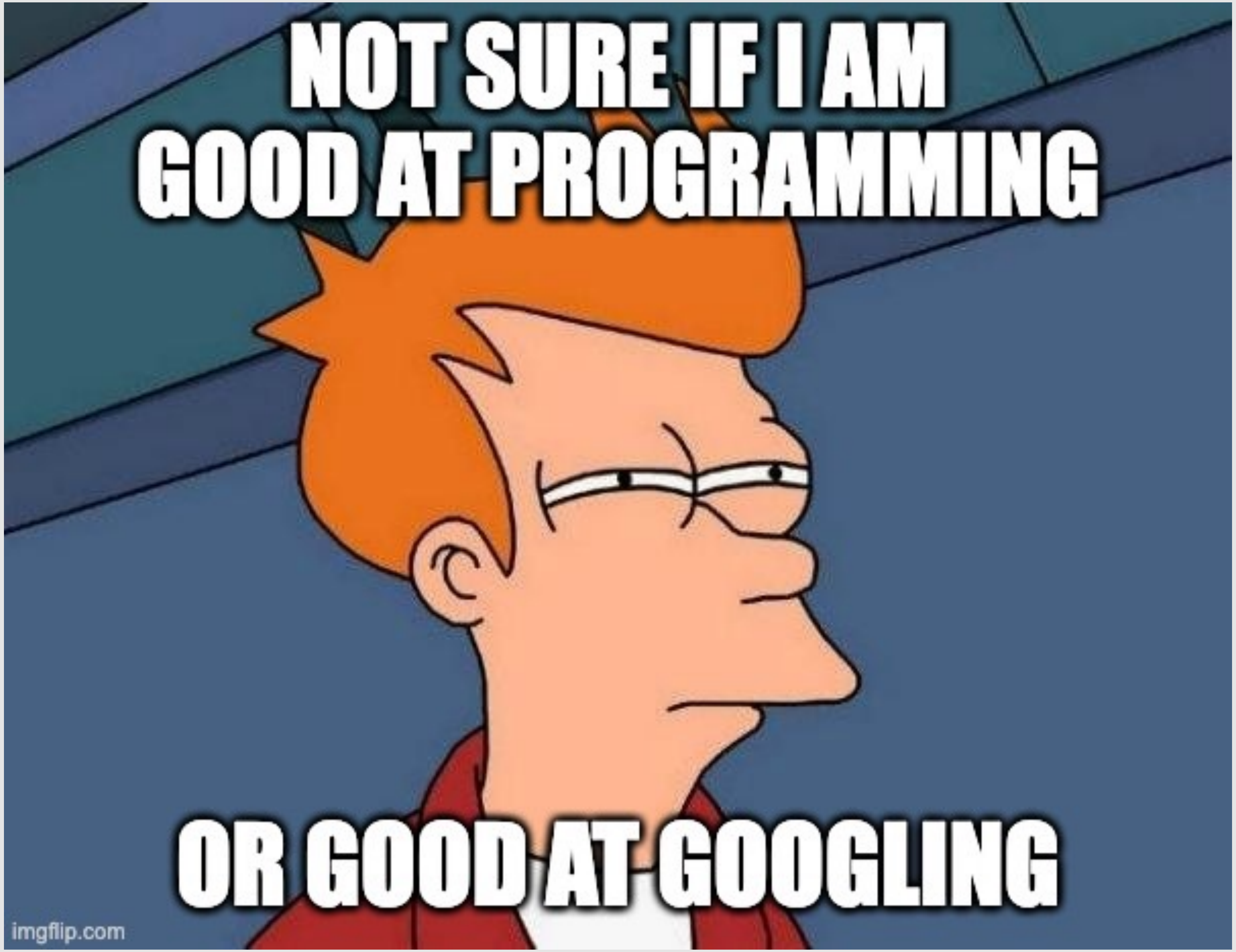
Note on learning to program

Especially for the beginners in the group:

- Some might think deep learning is too complicated and requires very complex maths they will never understand
- I don’t have a CS degree. My models are downloaded +20m times
- The main requirement is not formal education in CS or maths
- The main requirement is motivation to persist and to find solutions


NOT SURE IF I AM
GOOD AT PROGRAMMING
OR GOOD AT GOOGLING
imgflip.com

4

Learning to Google and to ChatGPT

- If you get an error → copy & paste it in Google
- If there is terminology or code you don't understand → ask Google
- Since 2023: ChatGPT makes debugging and learning even easier

4

Fine-tuning BERT

Fine-tune your own BERT model
on a real-world dataset

https://github.com/MoritzLaurer/summer-school-transformers-2023/tree/main

3_tune_bert.ipynb

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Fine-tuning BERT-NLI

Fine-tuning a universal model
on a real-world dataset

https://github.com/MoritzLaurer/summer-school-transformers-2023/tree/main

4_tune_bert_nli.ipynb

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Data centric AI

1. Data quality and data cleaning with CleanLab

https://github.com/MoritzLaurer/summer-school-transformers-2023/tree/main

5_data_quality_and_cleaning.ipynb

6

Data centric AI

2. Data annotation with Argilla

https://github.com/MoritzLaurer/summer-school-transformers-2023/tree/main

6_annotation_interface_argilla.ipynb

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LLM

Fine-tuning generative LLMs

Fine-tune a generative LLM
on a real-world dataset

https://github.com/MoritzLaurer/summer-school-transformers-2023/tree/main

7_tune_generative_llm.ipynb

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+/-

Risks of LLMs

What can go wrong?

https://docs.google.com/document/d/1GOl1CT1i0FL8sVWGGudHPLM9bOs7uARZYeRJe16At8Y/edit?usp=sharing

Your LLM project

What do you want to build with LLMs?

https://docs.google.com/document/d/1BHLobAJCn6aNN7a75vdgldyQN1ufrlEFr0T8CPz2YWs/edit?usp=sharing

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Use the wealth of online resources and build something!

Thank you for your attention!

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