

BioGPT: Generative Pre-trained Transformer for Biomedical Text Generation and Mining

Renqian Luo, Lai Sun, Yingce Xia, Tao Qin, Sheng Zhang, Hoifung Poon, and Tie-Yan Liu
Microsoft Research, October - 2022

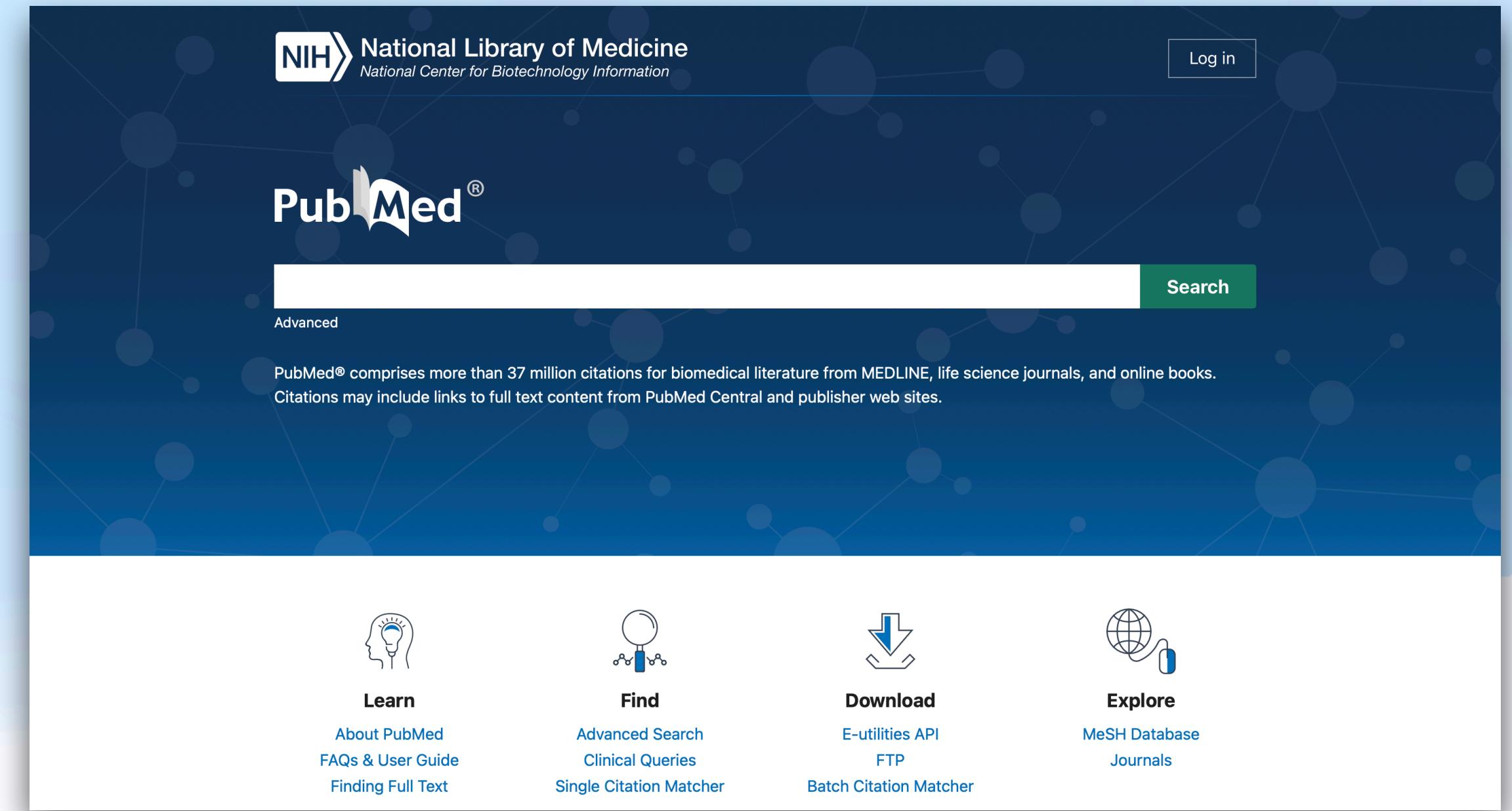
Bhautik Lukhi
Advanced AI in Biomedicine(Graded)
21st November, 2024

Agenda

- Motivation
- Biomedical NLP Tasks
- BERT and GPT
- Introduction to BioGPT
- Architecture, Training and Fine-tuning
- Results on Biomedical Tasks
- BioGPT in Action

Why

- Millions of Research Articles
- PubMed
- Semantic Scholar
- PMC
- Arxiv
-



PubMed



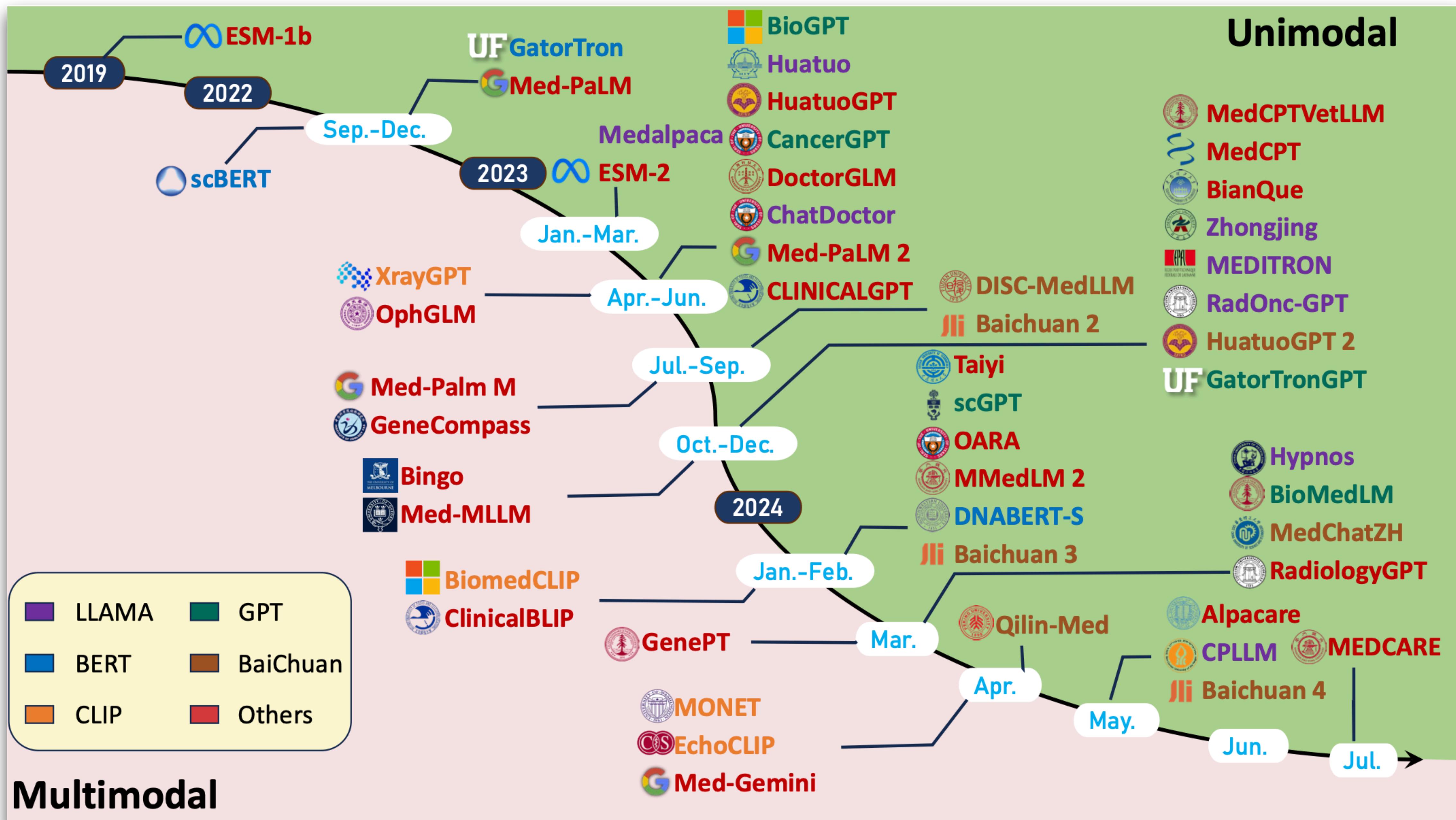
SEMANTIC SCHOLAR

NLP in Biomedicine

- Great at extracting insights from structured/unstructured biomedical text.
- Exceptional capabilities in complex language understanding and generation tasks.
- **Applications:**
 - ▶ Drug discovery
 - ▶ Clinical therapy enhancement
 - ▶ Pathology research

Biomedical NLP Tasks

- **Relation Extraction:** Identifying relationships between entities in text.
- **Question Answering:** Providing answers based on biomedical literature.
- **Document Classification:** Categorizing documents into predefined classes.
- **Text Generation:** Generating relevant biomedical text based on prompts.
- **Named Entity Recognition:** Identifying and classifying key entities.
- **Text Summarization:** Condensing lengthy articles into concise summaries.



Pre-trained models for Bio-medicine

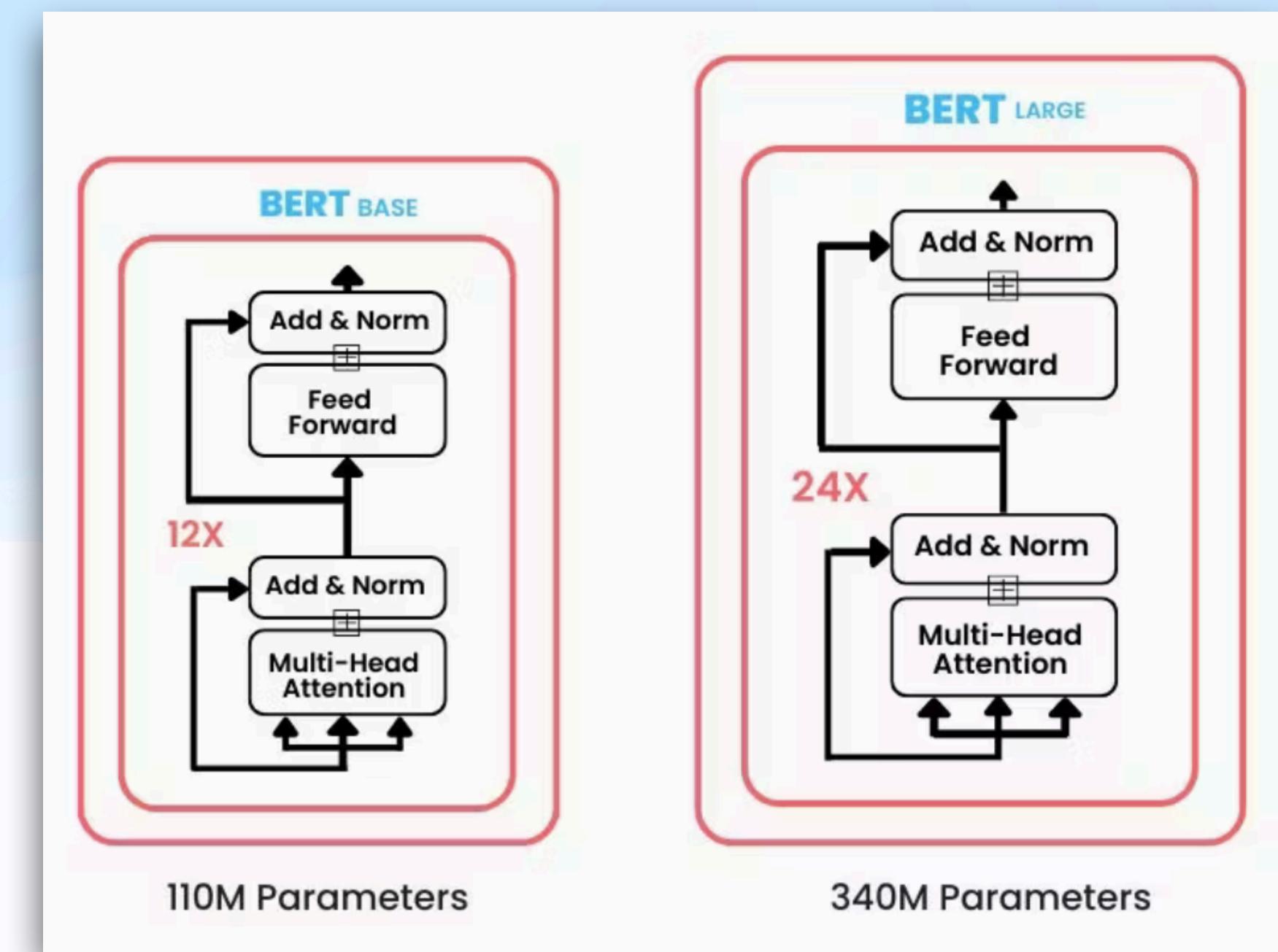
Model	Pros	Cons
BERT	Pretrained on massive data	General Domain
BioBERT	Continue pre-trained on bio domain	Shared vocab with general domain
BlueBERT	Continue pre-trained on bio domain	Shared vocab with general domain
SciBERT	Pretrained on Science domain	Out-domain knowledge
PubMedBERT	Pretrained on bio domain	Encoder only architecture
ELECTRAMed	Pretrained on bio domain	Encoder only architecture

*until November, 2022

BERT and GPT

BERT and GPT

- **BERT**: Pre-trained on English Wikipedia and BooksCorpus.
- **GPT**: Pre-trained Transformer pre-trained on BookCorpus.
- **Self-Supervision:**
 - ▶ Masked Language Modeling: Predicting masked words based on **full** context. 
 - ▶ Causal language modeling: Predicting the next word of the sentence based **only** on the past. 



BERT (Base) and BERT (Large).

Where BERT Lacks?

- **BERT's Constraints:**
 - Better at understanding rather than generating text.
- **GPT's Generative Edge:**
 - Better at language generation through a causal language modeling.
 - GPT-2 and GPT-3 enhance performance on multiple downstream tasks.
 - Multi-task and also Few-shot learner.

Why not use GPT Directly in Biomedicine?

- Even GPT-3 struggles with biomedical tasks due to the **Domain Shift**.
- **Previous Adaption Attempt:**
 - ▶ **DARE:** Pre-trained on limited data (**0.5M** abstracts) for data augmentation in relation extraction.
 - ▶ **But** results were limited.
 - ▶ **Task-Specific Adaptation(InstructGPT):** GPT model adapted for unconventional downstream clinical tasks.

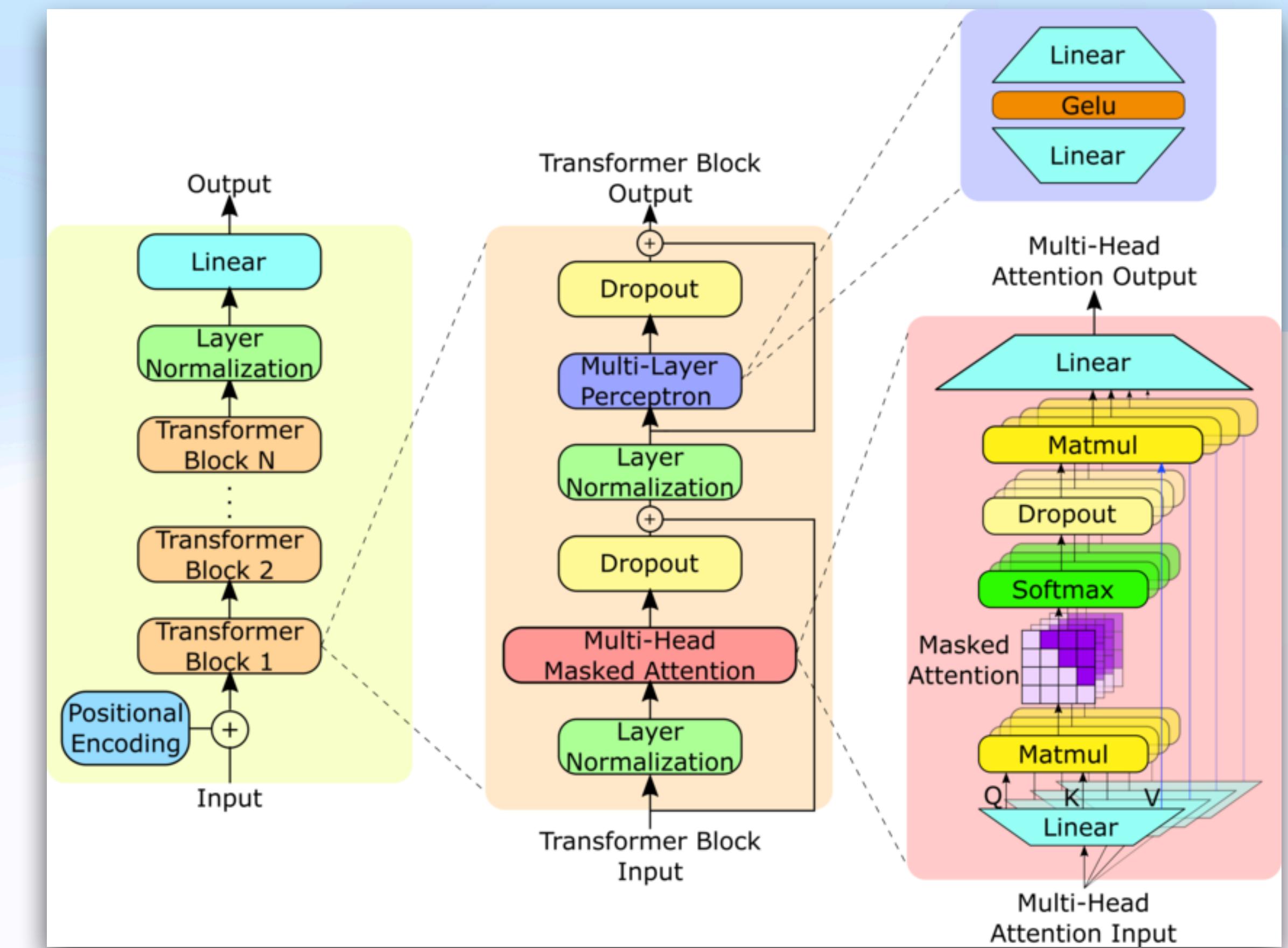
Introduction to BioGPT

What is BioGPT?

- A generative pre-trained Transformer for biomedical text, trained on **15M PubMed** abstracts.
- **Key Features:**
 - ▶ Combines generative modeling with biomedical relevance.
 - ▶ Can be used for Relation extraction, Question Answering, Document classification, and Text generation.

Architecture

- Based on the GPT-2_{medium} architecture.
- Features a Transformer decoder structure.
- **Key Components:**
 - Multi-head attention mechanism.
 - Trained end-to-end for optimized performance across various tasks.



GPT-2 Architecture (Yang et al., 2023)

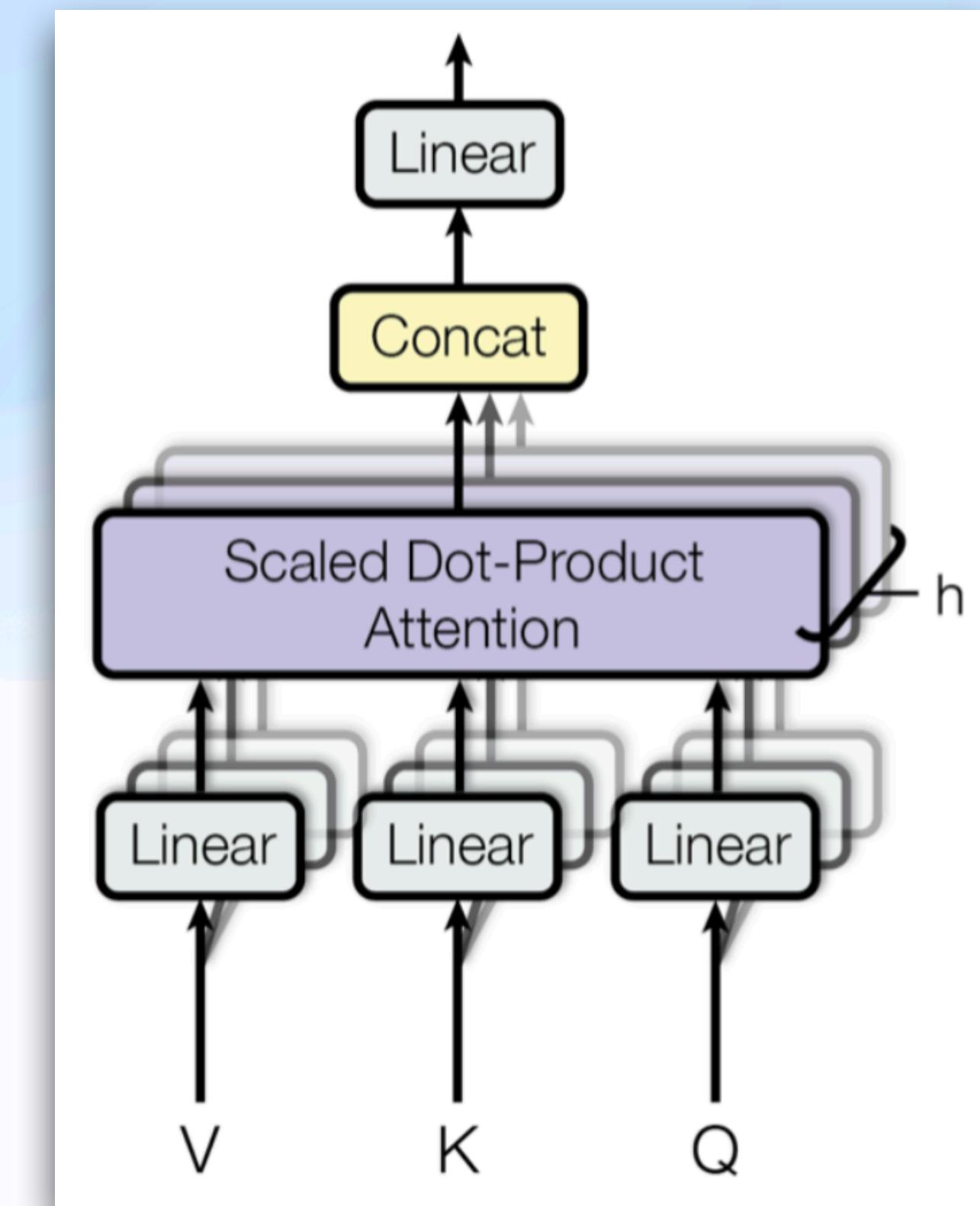
Multi-Head Attention Mechanism

- Runs multiple attention mechanisms in parallel.
- Outputs are concatenated and linearly transformed to match dimensions.

$$\text{Multihead}(Q, K, V) = \text{Concat}(\text{head}_1, \text{head}_2, \dots, \text{head}_h)W,$$

$$\text{head}_i = \text{softmax} \left(\frac{Q_i K_i^\top}{\sqrt{d}} \right) V_i$$

- Q, K, V : Queries, Keys, Values.
- W : Learnable parameter matrices.
- d : Dimensionality scaling factor.



Multi-Head Attention (Vaswani et al., 2017)

Training and Fine-tuning

Training Dataset

- Pre-trained on **15M PubMed abstracts**.
- Enables training effective language models with domain-specific knowledge.
- Bridge between general language understanding and biomedical text generation.
- **Key Characteristics:**
 - ▶ Diverse range of biomedical topics.
 - ▶ Continuously updated with newly published research.

Training

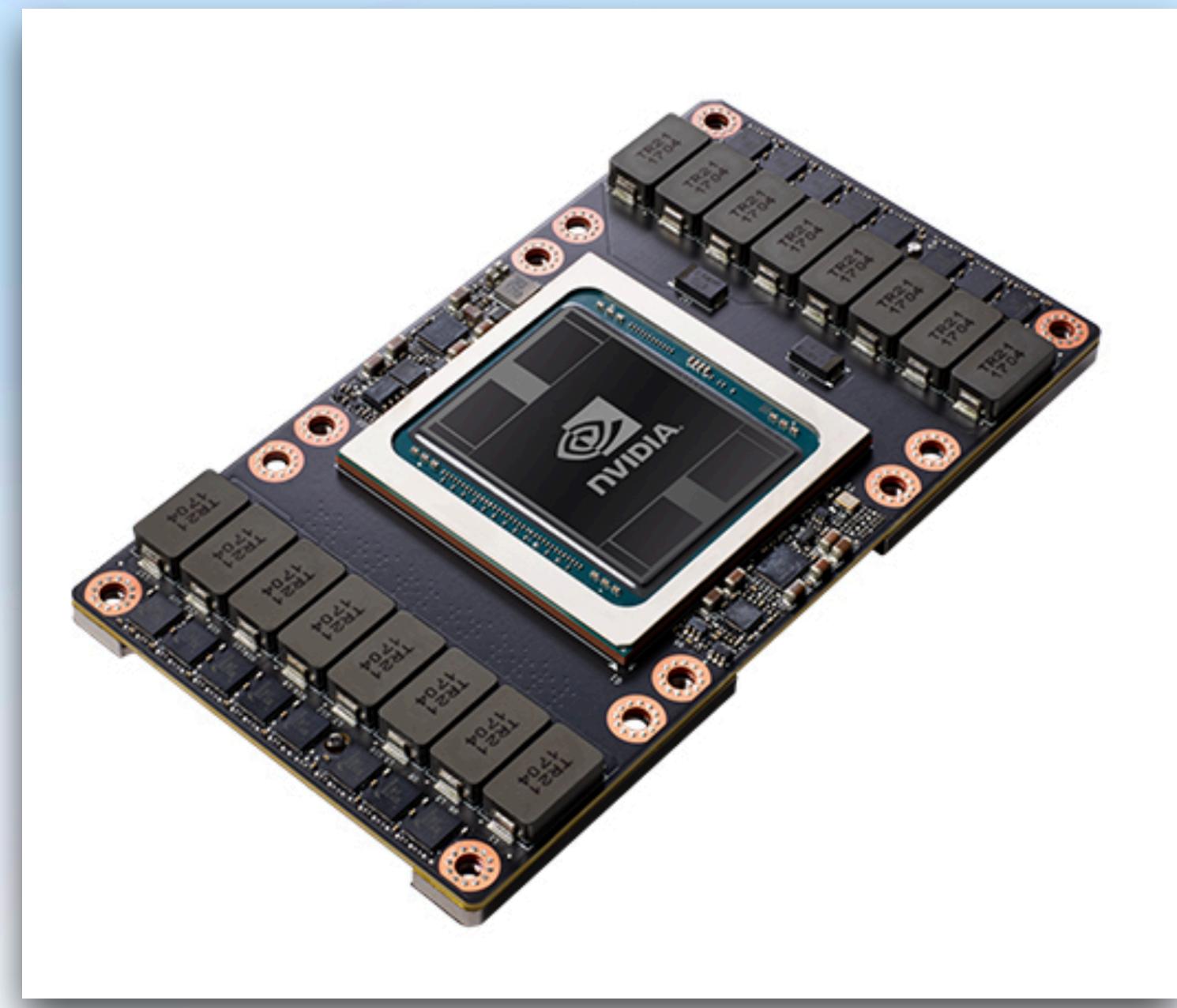
- Pre-trained using standard language modeling tasks.
- **Criteria:**
 - Minimize negative log-likelihood.

$$\min -\frac{1}{|D|} \sum_{i=1}^{|D|} \sum_{j=1}^{n_i} \log P(s_j | s_{j-1}, s_{j-2}, \dots, s_1)$$

- D : Dataset of sequences and s_j : token
- Effective batch size of **524,288 tokens**.
- **Adam** optimizer with a learning rate schedule.
- Employed a **warm-up phase(20,000 steps)** to stabilize the training.

Training Hardware

- Pre-trained on **8 NVIDIA V100 GPUs** for 200,000 steps.



NVIDIA V100 FOR NVLINK, from NVIDIA [website](#)

Vocabulary Development

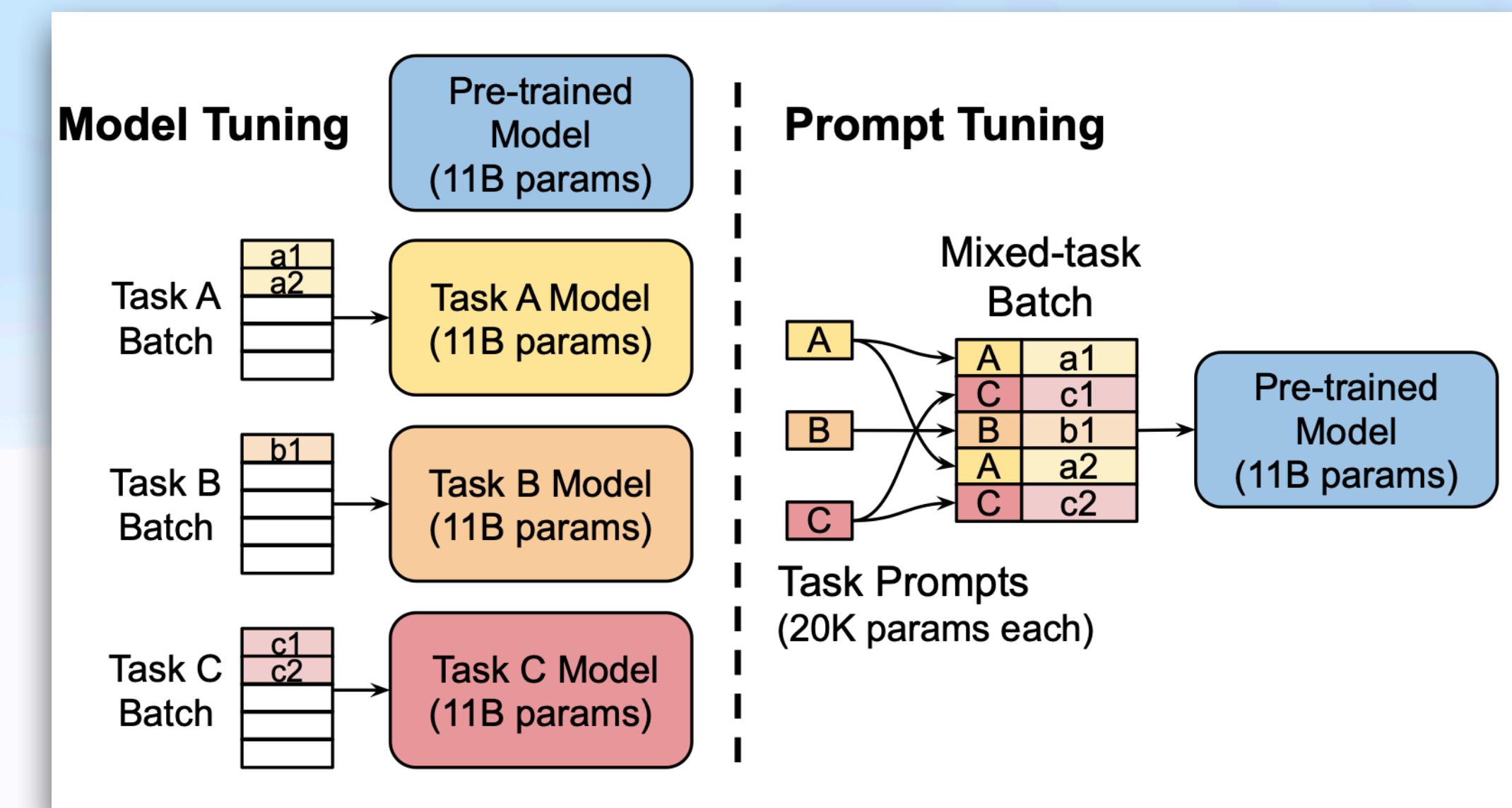
- **Why Domain-Specific Vocabulary?**
 - Language model's performance hinges on its vocabulary quality.
 - General vocabularies can complicate specialized biomedical terms.
- **Vocabulary Creation Process**
 - **Byte Pair Encoding (BPE):** Derives vocabulary directly from biomedical datasets.
 - **Final Vocabulary Size:** 42,384 tokens (50,257 for GPT)
- **Advantages:**
 - Better understanding of biomedical terminology.
 - More precise and contextually relevant text generation.

Fine-tuning Method Overview

- To adapt BioGPT for downstream tasks.
- **Key Adaptation:**
 - Convert labels into natural language sequences.
 - Maintains consistency with pre-training task format.
 - Avoids structured formats or special tokens for smoother semantics.

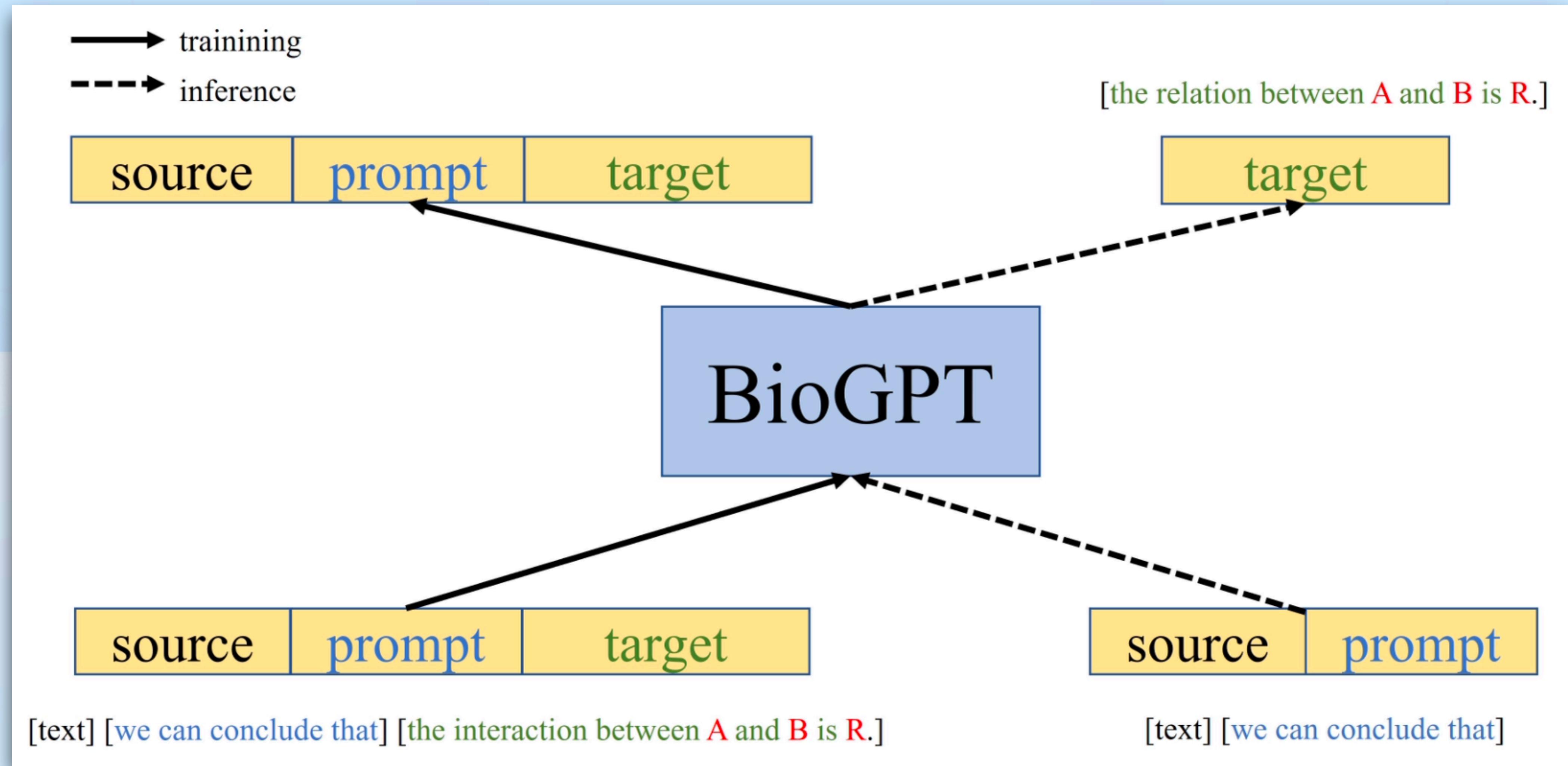
Prompt Based Fine-tuning Framework

- Simply concatenating source and target is ineffective.
- **Workaround:** prompts to guide the model in generating task-specific output.
- **Soft Prompts:** Continuous embeddings (virtual tokens) learned end-to-end.
 - ▶ Virtual tokens are placed between source and target sequences.



Model Tuning vs Prompt Tuning (Lester et al., 2021)

Prompt Based Fine-tuning Framework



Downstream Tasks

- **Relation Extraction:**
 - Key for biomedicine.
 - Focuses on generating relational triplets directly from text without intermediate annotations.
- **Question Answering (QA):**
 - Answering questions based on context.
 - Produce answer sequences, improving upon span prediction methods.
- **Document Classification:**
 - Classifying documents into predefined categories.
 - Leverages large pre-trained model for enhanced understanding and prediction.

Downstream Tasks

Task	Method	Dataset
Relation Extraction	GLRE, REBEL, seq2rel	KD-DTI, BC5CDR, DDI
Question Answering	QA-Net, LUKE, BERT, PubMedBERT, BioELECTRA, LinkBERT	PubMedQA, BioASQ
Document Classification	BERT, BlueBERT, SciBERT, SPECTER, PubMedBERT, BioELECTRA, LinkBERT	HoC, SciDocs

Summary of the downstream tasks for evaluation

BioGPT Variants

BioGPT

- 24-layer Transformer
- 347M parameters
- 15M PubMed abstracts
- Approx. 4B tokens

BioGPT_{large}

- 48- layer Transformer
- 1.57B parameters
- 15M PubMed abstracts + 6M PMC full paper
- Approx. 8B tokens

Results

1. Relation Extraction Task

- Extracting relationships between entities(triplets) in a single pass, without needing intermediate steps.

Model	Precision	Recall	F1
GLRE(gt+pred)	34.82	18.29	23.99
GLRE(pred+pred)	23.00	4.88	8.05
GPT-2	43.92	32.55	37.39
REBEL	34.28	39.49	36.70
REBEL _{pt}	40.94	21.20	27.94
Seq2rel	43.5	37.5	40.2
BioGPT	49.44	41.28	44.98
BioGPT⁺	49.52	43.25	46.17

Results on **BC5CDR** chemical-disease-relation task

Model	Precision	Recall	F1
Transformer + PubMedBERT-attn	25.35	24.14	24.19
GPT-2 _{medium}	30.53	27.87	28.45
REBEL	32.36	29.58	30.39
REBEL _{pt}	35.73	32.61	33.32
BioGPT	40.00	39.72	38.42

Results on **KD-DTI** drug-target-interaction task

Model	Precision	Recall	F1
GPT-2 _{medium}	23.39	31.93	24.68
REBEL	35.36	28.64	28.27
REBEL _{pt}	46.59	39.60	40.56
BioGPT	41.70	44.75	40.76

Results on **DDI** drug-drug-interaction task

2. Question Answering

- **Goal:** Answer questions using reference context.
- **Labels:** Yes, No, Maybe.

Model	Accuracy
PubMedBERT	55.8
BioELECTRa	64.2
BioLinkBERT _{base}	70.2
BioLinkBERT _{large}	72.2
BioGPT	78.2

Results on PubMedQA question answering task

3. Document Classification

- **Goal:** Classify document type based on text.
- **Target Sequence Format:** The type of this document is ‘label’.

Model	F1
BioBERT	81.54
PubMedBERT	82.32
PubMedBERT _{large}	82.70
BioLinkBERT _{base}	84.35
GPT-2 _{medium}	81.84
BioGPT	85.12

Results on **HoC** document classification task

Results Summary

Relation Extraction:

- Drug-Target Interaction (KD-DTI)
- Chemical-Disease Interaction (BC5CDR)
- Drug-Drug Interaction (DDI)
- **Up to 4%** improvement over all methods

Question Answering:

- PubMedQA
- **6.0%** improvement over previous best

Document Classification:

- HoC
- **3.28%** improvement over previous ones

BioGPT in Action

Drug-Target Interaction Extraction

The Janus family kinases (Jaks), Jak1, Jak2, Jak3, and Tyk2, form one subgroup of the non-receptor protein tyrosine kinases. They are involved in cell growth, survival, development, and differentiation of a variety of cells but are critically important for immune cells and hematopoietic cells. Data from experimental mice and clinical observations have unraveled multiple signaling events mediated by Jak in innate and adaptive immunity. Deficiency of Jak3 or Tyk2 results in defined clinical disorders, which are also evident in mouse models. A striking phenotype associated with inactivating Jak3 mutations is severe combined immunodeficiency syndrome, whereas mutation of Tyk2 results in another primary immunodeficiency termed autosomal recessive hyperimmunoglobulin E syndrome. In contrast, complete deletion of Jak1 or Jak2 in the mouse are not compatible with life and, unsurprisingly, do not have counterparts in human disease. However, activating mutations of each of the Jaks are found in association with malignant transformation, the most common being gain-of- function mutations of Jak2 in polycythemia vera and other myeloproliferative disorders. Our existing knowledge on Jak signaling pathways and fundamental work on their biochemical structure and intracellular interactions allow us to develop new strategies for controlling autoimmune diseases or malignancies by developing selective Jak inhibitors, which are now coming into clinical use. Despite the fact that Jaks were discovered only a little more than a decade ago, at the time of writing there are 20 clinical trials underway testing the safety and efficacy of Jak inhibitors.



- **Output:** the interaction between **pnus156804** and **janus kinase 3 (jak 3)** is **inhibitor**.
- **Structured Output:** <**pnus156804**, **janus kinase 3(jak 3)**, **inhibitor** >

Task: Find <drug, target, interaction> triplet given the document

Drug-Drug Interaction Extraction

An inhibitor of CYP2C8 (such as gemfibrozil) may increase the AUC of rosiglitazone and an inducer of CYP2C8 (such as rifampin) may decrease the AUC of rosiglitazone. Therefore, if an inhibitor or an inducer of CYP2C8 is started or stopped during treatment with rosiglitazone, changes in diabetes treatment may be needed based upon clinical response.



- **Output:** the interaction between **gemfibrozil** and **rosiglitazone** is **mechanism**; the interaction between **rifampin** and **rosiglitazone** is **mechanism**.
- **Structured output:** (**gemfibrozil**, **rosiglitazone**, **mechanism**), (**rifampin**, **rosiglitazone**, **mechanism**)

Task : Find <drug, drug, interaction> triplet given the document

Question Answering

Question: Do some US states have higher / lower injury mortality rates than others?

Context: this article examines the hypothesis that the six u.s. states with the highest rates of road traffic deaths (group 1 states) also had above-average rates of other forms of injury such as falling, poisoning, drowning, fire, suffocation, homicide, and suicide, and also for the retail trade and construction industries. the converse, second hypothesis, for the six states with the lowest rates of road traffic deaths (group 2 states) is also examined. data for these 12 states for the period 1983 to 1995 included nine categories of unintentional and four categories of intentional injury, seventy-four percent of the group 1 states conformed to the first hypothesis, and 85% of the group 2 states conformed to the second hypothesis, answer: group 1 states are likely to exhibit above-average rates for most other categories of injury death, whereas group 2 states are even more likely to exhibit below-average rates for most other categories of injury death.

Ground truth: Yes

BioGPT: the answer to the question given the context is **Yes**.

Zero-shot QA

Question: Can we measure mesopic pupil size with the cobalt blue light slit-lamp biomicroscopy method?

Context: [tl;dr: Some background introduction] The aim of this work is to assess a previously described slit-lamp biomicroscopy-based method (SLBM) for measuring pupil diameter and compare it to Colvard infrared pupillometry (CIP). Two examiners performed three repeated measurements with each instrument in 40 healthy eyes. We determined the agreement of SLBM and CIP, intraobserver and interobserver repeatabilities, and interobserver concordance (kappa) and SLBM ability for detecting pupil sizes over 6.0 mm. The mean (\pm standard deviation [SD]) pupil diameter was 5.81 ± 0.70 mm with SLBM and 6.26 ± 0.68 mm with CIP ($p=0.01$) averaging both examiner's results. Mean differences between the SLBM and CIP were -0.60 mm and -0.30 mm for each examiner using the average of the three readings ($p=0.02$), and they were very similar using the first reading.

Intraobserver reproducibility: the width of the 95% LoA ranged from 1.79 to 2.30 mm. The ICCs were 0.97 and 0.92 for SLBM, and 0.96 and 0.90 for CIP. Interobserver reproducibility, the width of the LOA ranged from 1.82 to 2.09 mm. Kappa statistics were 0.39 and 0.49 for the first and mean SLBM readings, respectively, and 0.45 for both the first and mean CIP readings. Sensitivity and specificity of SLBM for detection of pupils larger than 6 mm ranged from 55.56% to 73.68% and from 76.19% to 95.45%, respectively. The best tradeoff between sensitivity and specificity ranged from 5.4 mm to 6.2 mm.

Ground truth: No

BioGPT: The answer is that SLBM **is not a good alternative** to CIP for measuring pupil size.

Text Generation

Common Words

Input	Model	Text
Bicalutamide	GPT-2	<p>Bicalutamide, a synthetic bicalutamide derivative, was found to increase the cellular proliferation of <i>C. elegans</i> cells. This effect was not observed with the other synthetic bicalutamide derivatives. This is in line with our previous work which showed that bicalutamide increases the proliferation of <i>C. elegans</i> cells but not in the presence of synthetic bicalutamide.</p>
	BioGPT	<p>Bicalutamide (Casodex) is an androgen receptor (AR) antagonist approved for the treatment of metastatic castration-resistant prostate cancer (mCRPC) in patients who have progressed on or are ineligible for docetaxel chemotherapy, as well as for the treatment of early-stage prostate cancer in men who have not progressed on or are ineligible for docetaxel chemotherapy, as well as for the treatment of metastatic castration-sensitive prostate cancer (mCSPC) in men who have not progressed on or are ineligible for docetaxel chemotherapy.</p>

GPT-2 vs BioGPT when given relatively common names as input

Text Generation

Uncommon Words I

Xylazine GPT-2 Xylazine, the "active ingredient" in "bath salts" (see above) has been linked to numerous deaths, including those of former University of California, Berkeley, professor Andrew Anglin, who posted a video of himself having a bath filled with it.

BioGPT Xylazine is an alpha 2-adrenoceptor agonist that has been used as a sedative and analgesic in veterinary medicine for many years, but its effects on the cardiovascular system have not been extensively studied in the dog, and its effects on the central nervous system (CNS) have not been well characterized in the dog, despite the fact that xylazine has been widely used as a sedative and analgesic in veterinary medicine for more than 30 years.

Psoralen GPT-2 Psoralen, the city of the spiritualist, and had been given to him by God, who wished to show him the way of salvation, and to draw him back to the true life of Christ, and to bring him into communion with his fellow-man.

BioGPT Psoralen photochemotherapy (PUVA) is a well-established treatment for psoriasis, but its use is limited by the risk of skin cancer, particularly squamous cell carcinoma (SCC) of the head and neck (H & N), which is the most common site of skin cancer in the United States (US)

GPT-2 vs BioGPT when given somewhat uncommon names as input

Text Generation

Uncommon Words II

CP-673451	GPT-2	CP-673451) and 4-5-6-3-1-2-3-4-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28-29-30-31-32-33-34-35-36-37-38-39-40-41-42-43-44-45-46-47-48-49-50...
		CP-673451 is a potent, selective, and orally active inhibitor of human neutrophil elastase (HNE) and human cathepsin G (CatG) with in vitro and in vivo anti-inflammatory activity in a variety of animal BioGPT models of inflammation and in a model of acute lung injury (ALI) in the rat induced by intratracheal instillation of lipopolysaccharide (LPS) and tumor necrosis factor-alpha (TNF-alpha), a model of acute lung injury (ALI) in which neutrophils play an important role.
IIIB-021	GPT-2	IIIB-021A-2-1.pdf. Wright, C. (2002). "The War on Terror: A Legal Theory of Terrorist Attacks," in L.E.R. Wright, S.R. Warrick, and J.H. Rothman (Eds.), <i>The War on Terror: Essays in Honor of Michael T. Klare</i> (New York: Oxford University Press), 143-57.
		IIIB-021 is a novel, orally active, non-peptide bradykinin B2 receptor antagonist with potent and long-lasting anti-inflammatory activity in animal models of acute and chronic inflammation and in a rat model BioGPT of adjuvant-induced arthritis (AIA), an animal model of rheumatoid arthritis (RA), and in a rat model of collagen-induced arthritis (CIA), an animal model of collagen-induced arthritis (CIA), in which arthritis is induced by immunization with bovine type II collagen (CII).

GPT-2 vs BioGPT when given somewhat uncommon names as input

Text Generation

Keywords of interest

Input	Model	Text
COVID-19	GPT-2	COVID-19-0067-7 http://www.pinterest.com/pin/71178278499149422/ Black Widow: World War II's Greatest Widow? http://www.pinterest.com/pin/71177842668650112/
		COVID-19 is a global pandemic caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the causative agent of coronavirus disease 2019 (COVID-19), which has spread to more than 200 countries and territories, including the United States (US), Canada, Australia, New Zealand, the United Kingdom (UK), and the United States of America (USA), as of March 11, 2020, with more than 800,000 confirmed cases and more than 800,000 deaths.
SARS-CoV-2	GPT-2	SARS-CoV-2-CKM-T1-1/pdf/T1/SARS-CoV-2-CKM-T1-1.pdf Cancer http://www.cancer.gov/cancer-topics/programs/tox/tox-programs.html Other Research http://www.cdc.gov/cancer/cancer/index.html
		SARS-CoV-2 is the causative agent of COVID-19, a severe acute respiratory syndrome (SARS) that has infected more than 390,000 people worldwide and killed more than 250,000 people.

GPT-2 vs BioGPT when manually given keywords of interest (COVID-19 related terms)

Scaling to Larger Size

BioGPT_{large}

- Developed on **GPT-2 XL** architecture, **1.5B** parameters.
- Fine-tuned and evaluated for **enhanced performance** on downstream tasks.

Task	Metric	Performance
BC5CDR	F1	50.12
KD-DTI	F1	38.39
DDI	F1	44.89
PubMedQA	Accuracy	81.0
HoC	F1	84.40

BioGPT-Large fine-tuned on downstream tasks

Conclusion

- Built on the GPT-2 backbone, pre-trained on **15M PubMed** abstracts.
- **Pioneer** to adapt GPT effectively in Biomedicine domain.
- **Outperforms** GPT-2 in biomedical text generation.
- **State-of-the-Art** results on:
 - ▶ 3 relation extraction tasks.
 - ▶ 1 question answering task.
- Larger-scale BioGPT model on expanded biomedical datasets.

References

- <https://arxiv.org/pdf/2210.10341>
- <https://pubmed.ncbi.nlm.nih.gov/>
- <https://www.semanticscholar.org/>
- <https://arxiv.org/pdf/2409.00133>
- <https://vitalflux.com/bert-vs-gpt-differences-real-life-examples/>
- https://www.researchgate.net/figure/GPT-2-model-architecture-The-GPT-2-model-contains-N-Transformer-decoder-blocks-as-shown_fig1_373352176
- <https://arxiv.org/pdf/1706.03762>
- <https://www.nvidia.com/de-de/data-center/>

Any Questions?

Thank you for listening!