Large Language Models

Introduction and Recent Advances

ELL881 · AIL821

Tanmoy Chakraborty
Associate Professor, IIT Delhi
https://tanmoychak.com/

Semester 1, 2024-2025

Course Instructors

Tanmoy Chakraborty
IIT Delhi

Yatin Nandwani
IBM Research

Dinesh Raghu
IBM Research

Sourish Dasgupta
DA-IICT

Gaurav Pandey
IBM Research

Manish Gupta
Microsoft

Course TA

Anwoy Chatterjee
PhD student, IIT Delhi

Course Directives

- Slot **H** (Mon, Wed: 11-12; Thu: 12-13)
- Website: https://lcs2-iitd.github.io/ELL881-AIL821-2401/
- YouTube: https://www.youtube.com/@lcs2575
- Room: II-301

Marks distribution (tentative)

- Minor: 15%
- Major: 25%
- Quiz (2): 10%
- Assignment (1): 20%
- Mini-project: 30% (group-wise)

- **Audit**: B- (threshold to pass the course)
- **Grading Scheme**: TBD

Course Project

- Some problem statements, and datasets will be floated soon*
- Each group should consist of 1-2 students
- **Best Project Award**
- You need to
  - develop models
  - evaluate your models
  - prepare presentation
  - write tech report

Students are encouraged to publish their projects in good conferences/journals

* You are welcome to propose a new idea if you find it fascinating to be qualified for a course project. Instructor opines!

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Deliverables:

1. Final project report (**15%**), 8 pages ACL format. Encouraged to arxiv
2. Repo of dataset and source code (**5%**)
3. Final project presentation (**10%**)

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Do Not Plagiarize !

Academic Integrity is of utmost importance. If anyone is found cheating/plagiarizing, it will result in negative penalty (and possibly even more: an F grade or even DisCo).

Collaborate. But do NOT cheat.

- Assignments to be done individually.
- Do not share any part of code.
- Do not copy any part of report from any online resources or published works.
- If you reuse other’s works, always cite.
- If you discuss with others about assignment or outside your group for project, mention their names in the report.
- Do not use GenAI tools (like, ChatGPT).

We will check for pairwise plagiarism in submitted assignment code files among you all.

We will also check the probability of any submitted content being AI generated.

Project reports will be checked for plagiarism across all web resources.

Course Content

- This is an **advanced graduate course** and we will be teaching and discussing state-of-the-art papers about large language models.
- The course is mostly presentation- and discussion-based and all the students are expected to come to the class regularly and participate in discussion

Course Content

Basics

- Introduction
- Intro to NLP
- Intro to Language Models (LMs)
- Word Embeddings (Word2Vec, GloVE)
- Neural LMs (CNN, RNN, Seq2Seq, Attention)

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Architecture

- Intro to Transformer
- Decoder-only LM, Prefix LM, Decoding strategies
- Encoder-only LM, Encoder-decoder LM
- Advanced Attention
- Mixture of Experts

Course Content

Basics	Architecture	Learnability
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Course Content

Basics	Architecture	Learnability	User Acceptability	Ethics and Misc.
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Pre-Requisites

- Excitement about language!
- Willingness to learn

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Mandatory	Desirable
• Data Structures & Algorithms • Machine Learning • Python programming	• NLP • Deep learning

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• Data Structures & Algorithms • Machine Learning • Python programming	• NLP • Deep learning

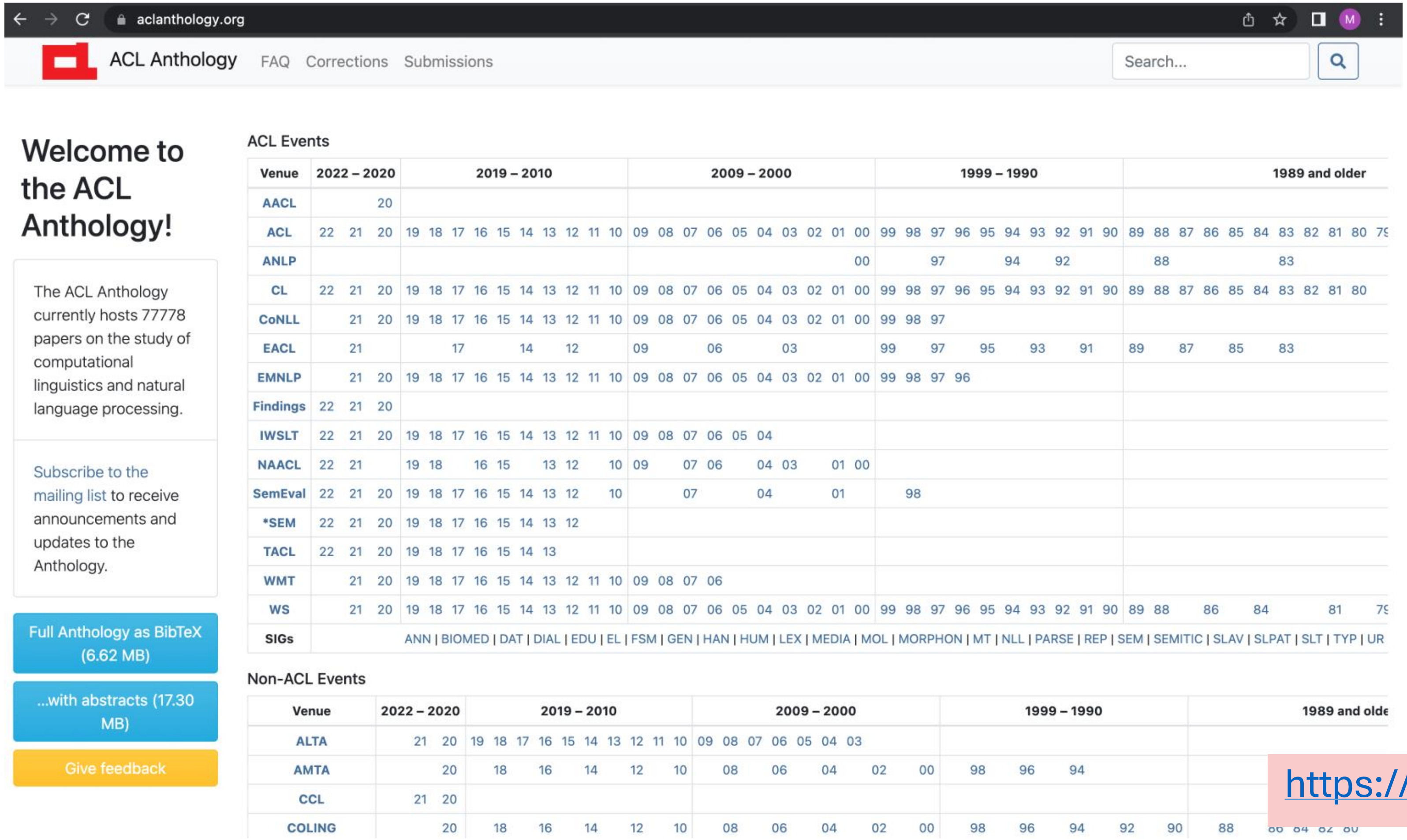
This course will NOT cover:

- Details of NLP (ELL884: https://sites.google.com/view/ell881), Machine Learning and Deep Learning
- Coding practice
- Generative models for modalities other than text

Reading and Reference Materials

- Books (optional reading)
  - Speech and Language Processing, Dan Jurafsky and James H. Martin
https://web.stanford.edu/~jurafsky/slp3/
  - Foundations of Statistical Natural Language Processing, Chris Manning and Hinrich Schütze
  - Natural Language Processing, Jacob Eisenstein
https://github.com/jacobeisenstein/gt-nlp-class/blob/master/notes/eisenstein-nlp-notes.pdf
  - A Primer on Neural Network Models for Natural Language Processing, Yoav Goldberg
http://u.cs.biu.ac.il/~yogo/nnlp.pdf
- Journals
  - Computational Linguistics, Natural Language Engineering, TACL, JMLR, TMLR, etc.
- Conferences
  - ACL, EMNLP, NAACL, COLING, AAAI, IJCNLP, ICML, NeurIPS, ICLR, WWW, KDD, SIGIR, etc.

Research Papers Repository



https://aclanthology.org/

Research Papers Repository

arXiv.org > cs > cs.CL

Computation and Language

Authors and titles for recent submissions

- Wed, 19 Aug 2020
- Tue, 18 Aug 2020
- Mon, 17 Aug 2020
- Fri, 14 Aug 2020
- Thu, 13 Aug 2020

[total of 84 entries: **1-25** | 26-50 | 51-75 | 76-84]
[showing 25 entries per page: fewer | more | all]

Wed, 19 Aug 2020

[1] **arXiv:2008.07905** [**pdf**, **other**]
Glancing Transformer for Non-Autoregressive Neural Machine Translation
Lihua Qian, Hao Zhou, Yu Bao, Mingxuan Wang, Lin Qiu, Weinan Zhang, Yong Yu, Lei Li
Comments: 11 pages, 3 figures, 4 tables
Subjects: **Computation and Language (cs.CL)**

[2] **arXiv:2008.07880** [**pdf**, **other**]
COVID-SEE: Scientific Evidence Explorer for COVID-19 Related Research
Karin Verspoor, Simon Šuster, Yulia Otmakhova, Shevon Mendis, Zenan Zhai, Biaoyan Fang, Jey Han Lau, Timothy Bal
Comments: COVID-SEE is available at this http URL
Subjects: **Computation and Language (cs.CL)**; Information Retrieval (cs.IR)

[3] **arXiv:2008.07772** [**pdf**, **other**]
Very Deep Transformers for Neural Machine Translation
Xiaodong Liu, Kevin Duh, Liyuan Liu, Jianfeng Gao
Comments: 6 pages, 3 figures and 3 tables
Subjects: **Computation and Language (cs.CL)**

[4] **arXiv:2008.07723** [**pdf**, **other**]
NASE: Learning Knowledge Graph Embedding for Link Prediction via Neural Architecture Search
Xiaoyu Kou, Bingfeng Luo, Huang Hu, Yan Zhang
Comments: Accepted by CIKM 2020, short paper
Subjects: **Computation and Language (cs.CL)**

https://arxiv.org/list/cs.CL/recent

Acknowledgements (Non-exhaustive List)

- Advanced NLP, Graham Neubig http://www.phontron.com/class/anlp2022/
- Advanced NLP, Mohit Iyyer https://people.cs.umass.edu/~miyyer/cs685/
- NLP with Deep Learning, Chris Manning, http://web.stanford.edu/class/cs224n/
- Understanding Large Language Models, Danqi Chen https://www.cs.princeton.edu/courses/archive/fall22/cos597G/
- Natural Language Processing, Greg Durrett https://www.cs.utexas.edu/~gdurrett/courses/online-course/materials.html
- Large Language Models: https://stanford-cs324.github.io/winter2022/
- Natural Language Processing at UMBC, https://laramartin.net/NLP-class/
- Computational Ethics in NLP, https://demo.clab.cs.cmu.edu/ethical_nlp/
- Self-supervised models, CS 601.471/671: Self-supervised Models (jhu.edu)
- WING.NUS Large Language Models, https://wing-nus.github.io/cs6101/
- And many more…

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Language Model gives the probability distribution over a sequence of tokens.

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Language Model

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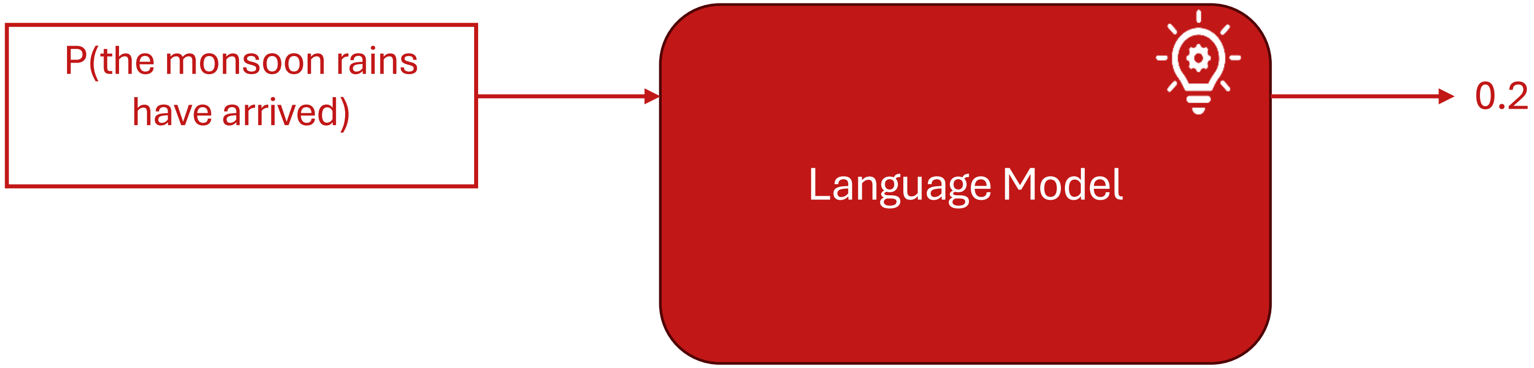

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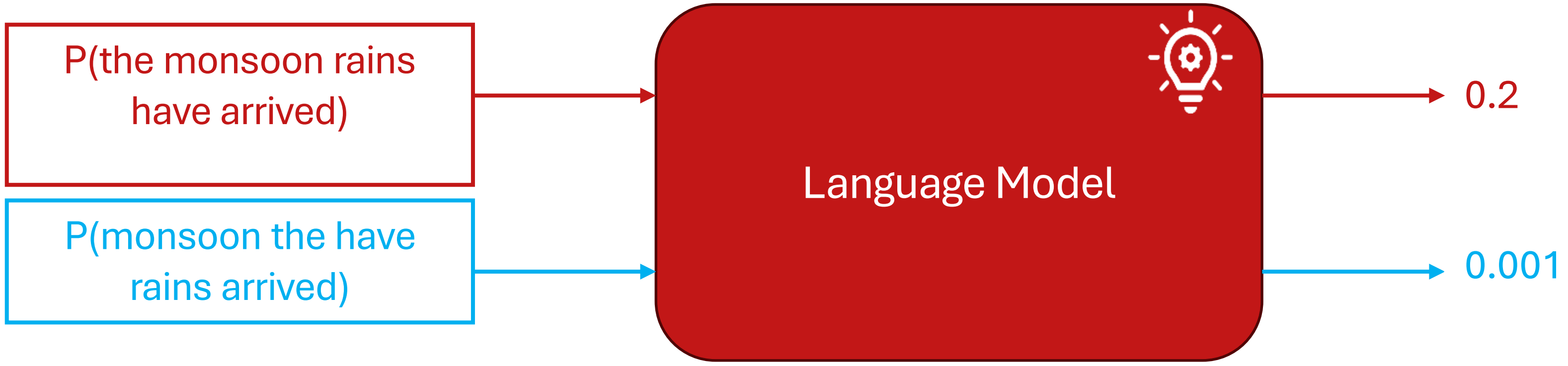

Vocabulary

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LMs can 'Generate' Text !

- Consider a sequence of tokens $\{x_1, x_2, \ldots, x_L\}$,where $x_1, x_2, \ldots, x_L$ are in vocabulary *V*
- Notation: $P(x_1, x_2, \ldots, x_L) = P(x_{1:L})$
- Using the **chain rule of probability:**

$$P(x_{1:L}) = P(x_1).P(x_2|x_1).P(x_3|x_1, x_2) \ldots P(x_L|x_{L-1}) = \prod_{i=1}^{L} P(x_i|x_{1:i-1})$$

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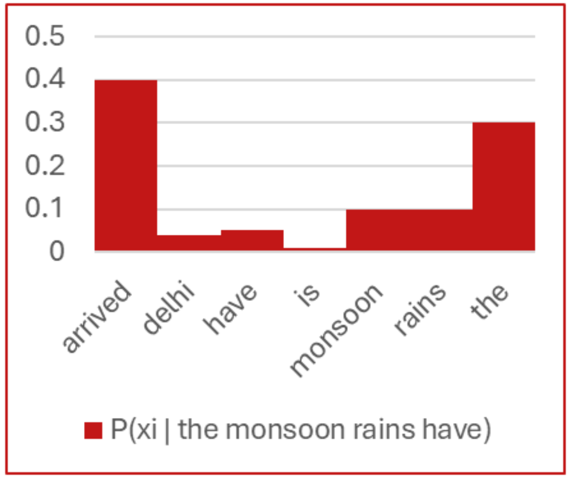

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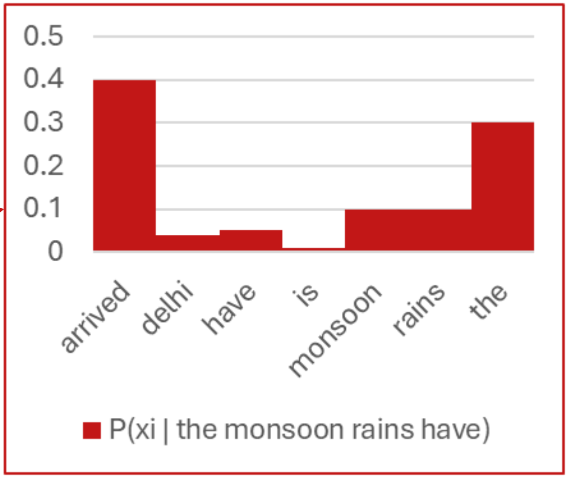

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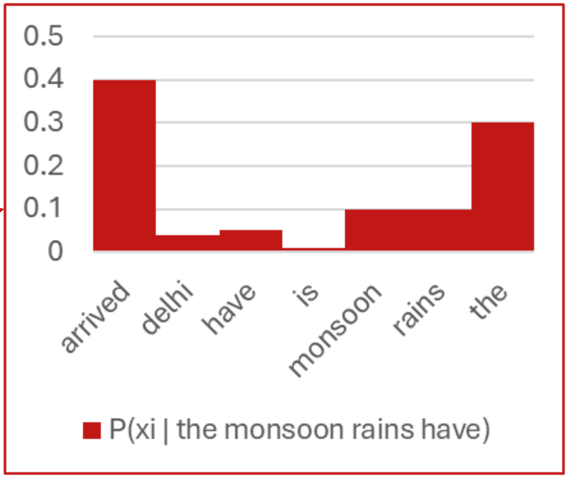

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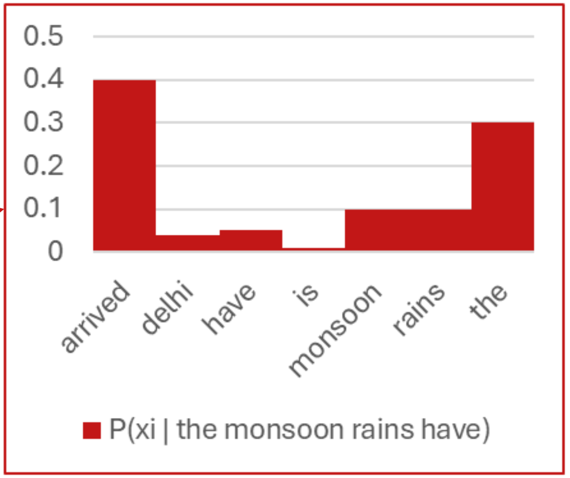

Auto-regressive LMs calculate this distribution efficiently, e.g. using 'Deep' Neural Networks

$x_i \sim P(x_i \mid x_{1:i-1})$

‘Large’ Language Models

The ‘Large’ in terms of model's size (# parameters) and massive size of training dataset.

Model	Organization	Date	Size (# params)
ELMo	AI2	Feb 2018	94,000,000
GPT	OpenAI	Jun 2018	110,000,000
BERT	Google	Oct 2018	340,000,000
XLM	Facebook	Jan 2019	655,000,000
GPT-2	OpenAI	Mar 2019	1,500,000,000
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Megatron-LM	NVIDIA	Sep 2019	8,300,000,000
T5	Google	Oct 2019	11,000,000,000
Turing-NLG	Microsoft	Feb 2020	17,000,000,000
GPT-3	OpenAI	May 2020	175,000,000,000
Megatron-Turing NLG	Microsoft, NVIDIA	Oct 2021	530,000,000,000
Gopher	DeepMind	Dec 2021	280,000,000,000

Model sizes have increased by an order of **5000x** over just the last 4 years !!!

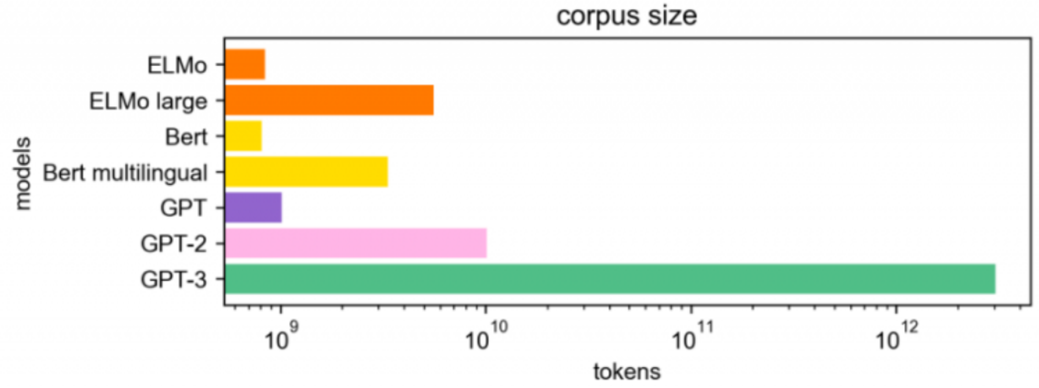

Image source: https://hellofuture.orange.com/en/the-gpt-3-language-model-revolution-or-evolution/

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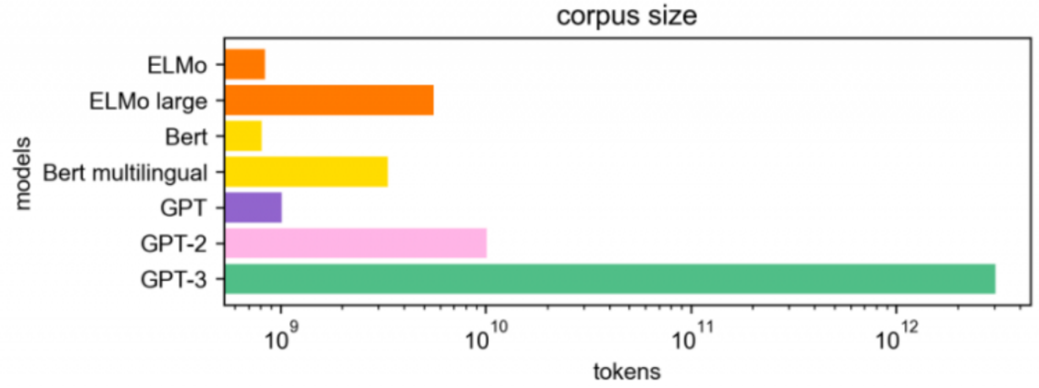

Other recent models: PaLM (540B), OPT (175B), BLOOM (176B), Gemini-Ultra (1.56T), GPT-4 (1.76T)

Disclaimer: For API-based models like GPT-4/Gemini-Ultra, the number of parameters are not announced officially – these are rumored numbers as on the web

Image source: https://hellofuture.orange.com/en/the-gpt-3-language-model-revolution-or-evolution/

LLMs in AI Landscape

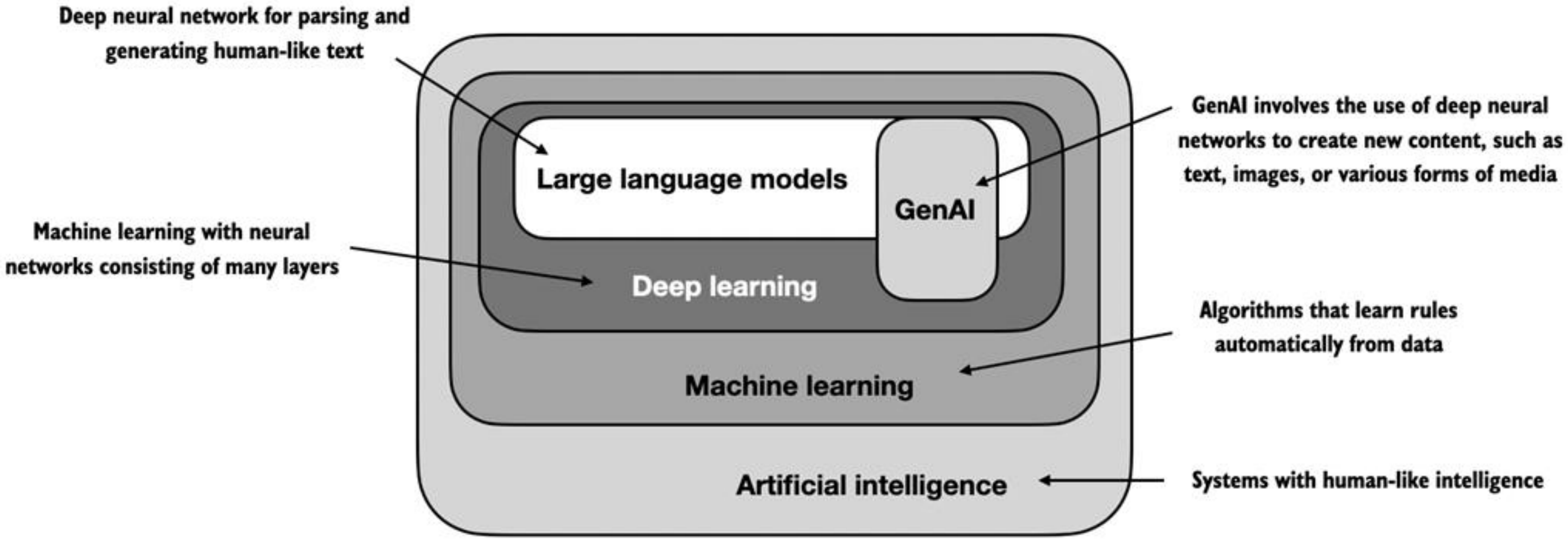

Image source: https://www.manning.com/books/build-a-large-language-model-from-scratch

Evolution of (L)LMs

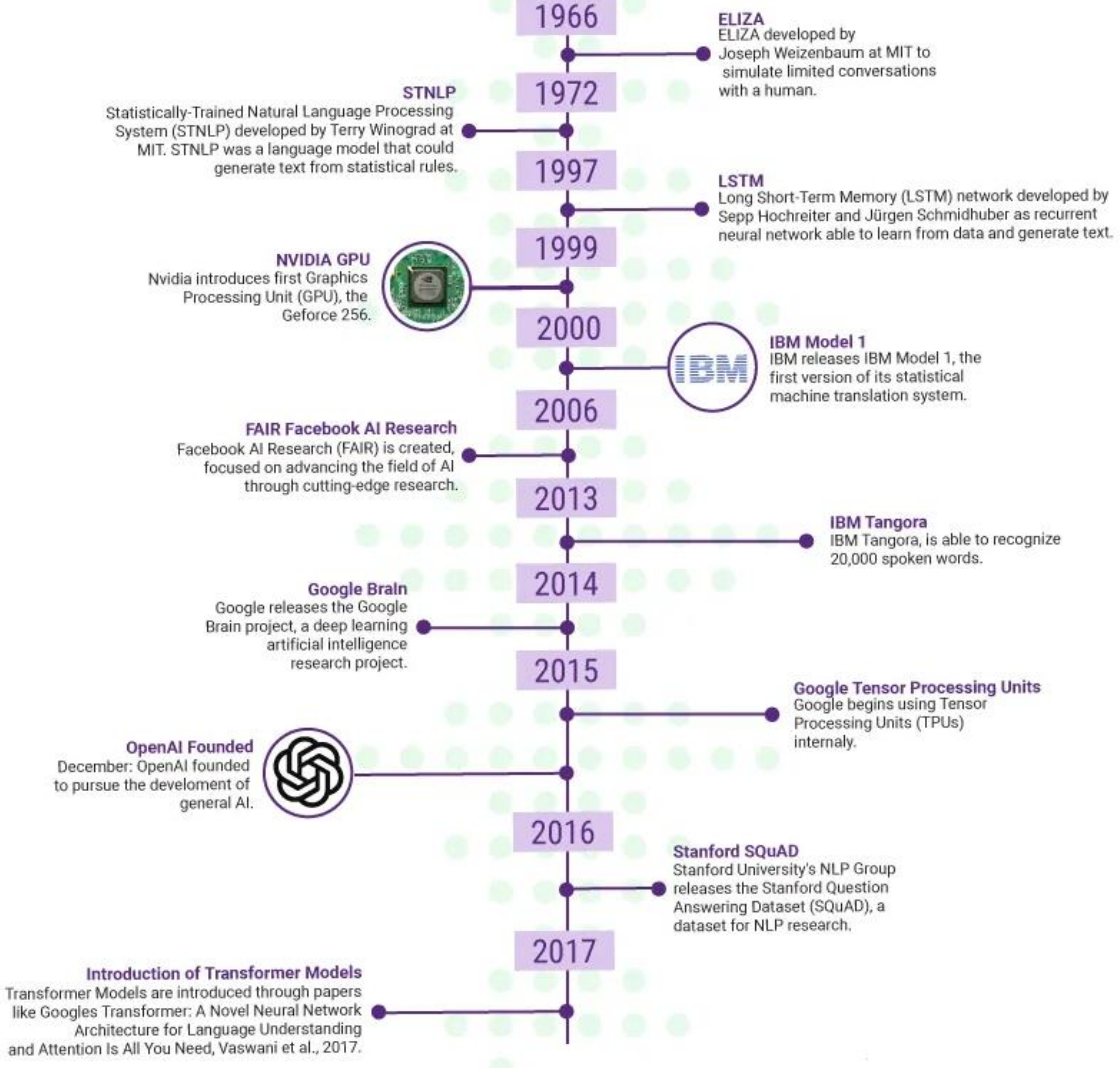

Image source: https://synthedia.substack.com/p/a-timeline-of-large-language-model

Post-Transformers Era

The LLM Race

Google Designed Transformers: But Could it Take Advantage?

Transformers (2017)

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com

Noam Shazeer* Google Brain noam@google.com

Niki Parmar* Google Research nikip@google.com

Jakob Uszkoreit* Google Research usz@google.com

Llion Jones* Google Research llion@google.com

Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu

Łukasz Kaiser* Google Brain lukaszkaiser@google.com

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

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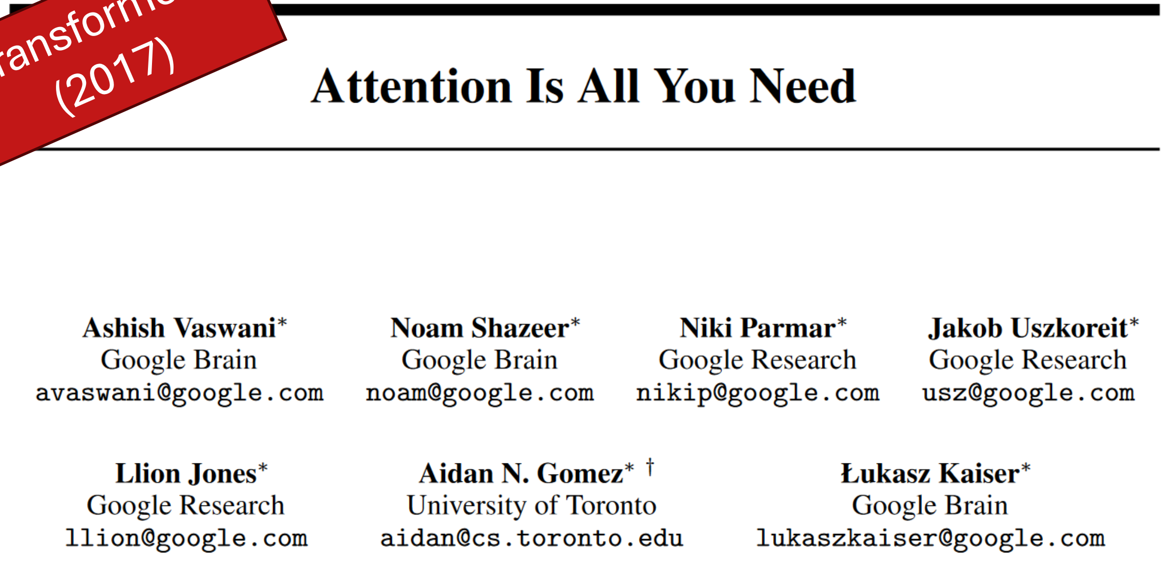
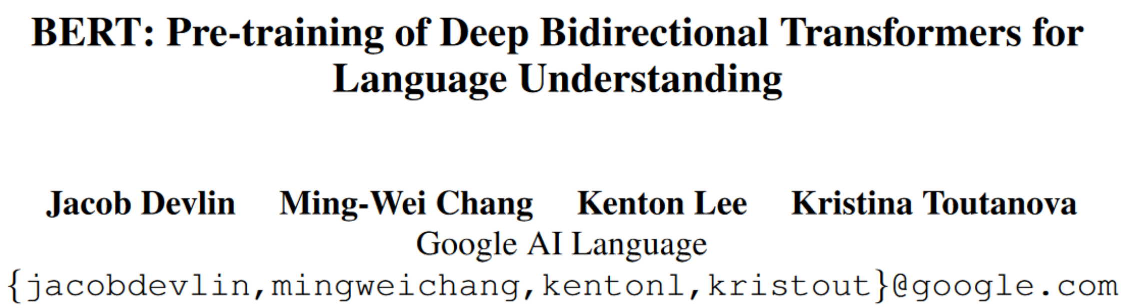


BERT (2018)



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BERT (2018)

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

The beginning of use of Transformer as Language Representation Models.

BERT achieved SOTA on 11 NLP tasks.

Google Designed Transformers: But Could it Take Advantage?

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Illia Polosukhin* ‡ illia.polosukhin@gmail.com

BERT (2018)

DistilBERT, TinyBERT, MobileBERT

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

The beginning of use of Transformer as Language Representation Models.

BERT achieved SOTA on 11 NLP tasks.

However, someone was waiting for the right opportunity!!

Guess Who?

However, someone was waiting for the right opportunity!!

OpenAI

OpenAI Started Pushing the Frontier

OpenAI

Improving Language Understanding by Generative Pre-Training

Alec Radford OpenAI alec@openai.com

Karthik Narasimhan OpenAI karthikn@openai.com

Tim Salimans OpenAI tim@openai.com

Ilya Sutskever OpenAI ilyasu@openai.com

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- Use of decoder-only architecture
- The idea of generative pre-training over large corpus

The Beginning of Scale

GPT-2 (2019)

Language Models are Unsupervised Multitask Learners

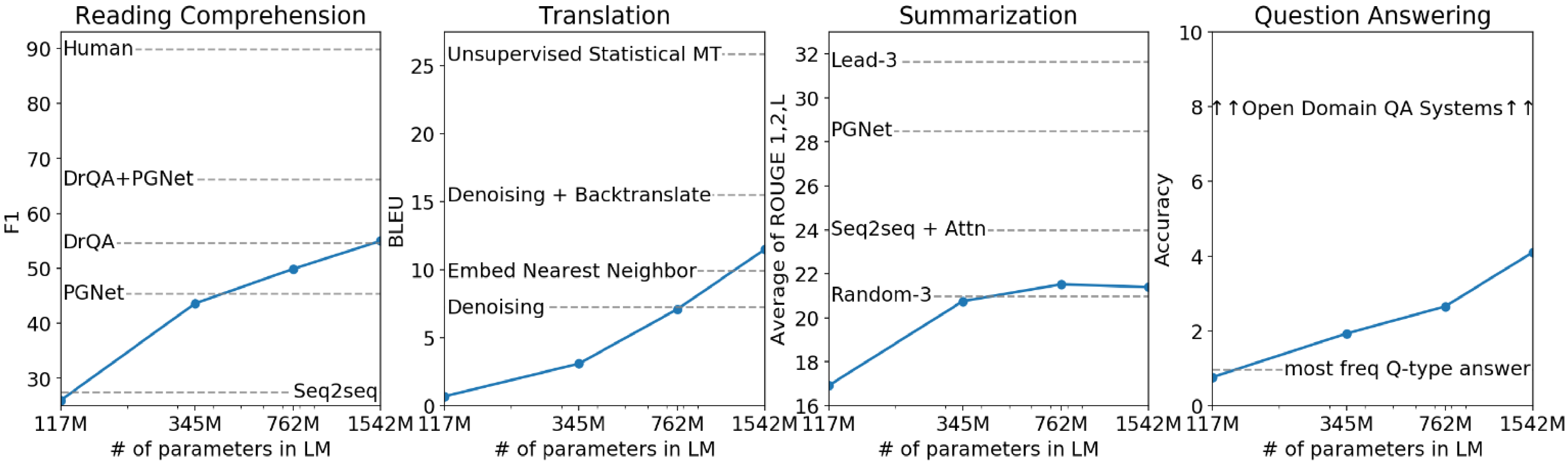
Alec Radford [*1] Jeffrey Wu [*1] Rewon Child [1] David Luan [1] Dario Amodei [**1] Ilya Sutskever [**1]

- GPT-1 (117 M) → GPT-2 (1.5 B) **13x increase in # parameters**
- Minimal changes (some LayerNorms added, modified weight initialization)
- Increase in context length: GPT-1 (512 tokens) → GPT-2 (1024 tokens)

The Beginning of Scale

GPT-2 (2019)

Performance boosts across tasks



What Was Google Developing Parallelly?

T5 (2019)

Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

Colin Raffel* CRAFFEL@GMAIL.COM

Noam Shazeer* NOAM@GOOGLE.COM

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Peter J. Liu PETERJLIU@GOOGLE.COM

Google, Mountain View, CA 94043, USA

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- Similar broader goal of converting all text-based language problems into a text-to-text format.
- Used **Encoder-Decoder Architecture**.
- Pre-training strategy differs from GPT
  - Strategy more similar to BERT

Google, Mountain View, CA 94043, USA

Was It Only Google vs OpenAI?
Where did **Meta** Stand?

Was It Only Google vs OpenAI? Where did **Meta** Stand?

RoBERTa (2019)

RoBERTa: A Robustly Optimized BERT Pretraining Approach

Yinhan Liu[*§] **Myle Ott**[*§] **Naman Goyal**[*§] **Jingfei Du**[*§] **Mandar Joshi**[†]
Danqi Chen[§] **Omer Levy**[§] **Mike Lewis**[§] **Luke Zettlemoyer**[†§] **Veselin Stoyanov**[§]

[†] Paul G. Allen School of Computer Science & Engineering,
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fb.com

- Replication study of BERT pretraining
- Measured the impact of many key hyperparameters and training data size.
- **Found that BERT was significantly undertrained**, and can match or exceed the performance of every model published after it.

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XLM (2019)

Cross-lingual Language Model Pretraining

Guillaume Lample*
Facebook AI Research
Sorbonne Universités
glample@fb.com

Alexis Conneau*
Facebook AI Research
Université Le Mans
aconneau@fb.com

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XLM (2019)

Cross-lingual Language Model Pretraining

Guilla... ...au*
Facebo... ...earch
Sorbon... ...lans
glamp... ...com

- Proposed methods to learn **cross-lingual language models (XLMs)**
- Obtained SOTA on:
  - cross-lingual classification
  - unsupervised and supervised machine translation

OpenAI Continues to Scale

GPT-3 (2020)

Language Models are Few-Shot Learners

Tom B. Brown* Benjamin Mann* Nick Ryder* Melanie Subbiah*

Jared Kaplan† Prafulla Dhariwal Arvind Neelakantan Pranav Shyam Girish Sastry

Amanda Askell Sandhini Agarwal Ariel Herbert-Voss Gretchen Krueger Tom Henighan

Rewon Child Aditya Ramesh Daniel M. Ziegler Jeffrey Wu Clemens Winter

Christopher Hesse Mark Chen Eric Sigler Mateusz Litwin Scott Gray

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OpenAI

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OpenAI

175 B parameters !

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OpenAI

175 B parameters !

OpenAI stops open-sourcing!!

Google Starts Scaling too (But is it Late) !

PaLM (2022)

PaLM: Scaling Language Modeling with Pathways

Aakanksha Chowdhery[*] Sharan Narang[*] Jacob Devlin[*]
Maarten Bosma Gaurav Mishra Adam Roberts Paul Barham
Hyung Won Chung Ch ker Schuh Kensen Shi
Sasha Tsvyashchenk ker Barnes Yi Tay
Noam Shazeer[‡] Vino Du Ben Hutchinson
Reiner Pope Jan ard Guy Gur-Ari
Pengcheng Yin To mawat Sunipa Dev
Henryk Michalewski Xavier Garcia Vedant Misra Kevin Robinson Liam Fedus
Denny Zhou Daphne Ippolito David Luan[‡] Hyeontaek Lim Barret Zoph
Alexander Spiridonov Ryan Sepassi David Dohan Shivani Agrawal Mark Omernick
Andrew M. Dai Thanumalayan Sankaranarayana Pillai Marie Pellat Aitor Lewkowycz
Erica Moreira Rewon Child Oleksandr Polozov[†] Katherine Lee Zongwei Zhou
Xuezhi Wang Brennan Saeta Mark Diaz Orhan Firat Michele Catasta[†] Jason Wei
Kathy Meier-Hellstern Douglas Eck Jeff Dean Slav Petrov Noah Fiedel

Google Research

540 B parameters !

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Kathy Mei … Noah Fiedel
Google Research

540 B parameters !

Google follows OpenAI in stopping open-sourcing !

It's now the "LLM Race"

2021-2022: A Flurry of LLMs

Microsoft
NVIDIA
Megatron-Turing NLG

Gopher

DeepMind
Chinchilla AI

LaMDA

CODEGEN

OpenAI
Codex

Google AI
MINERVA
MODEL FOR
QUANTITATIVE REASONING
PROBLEMS SOLVING

Meta Promotes Open-sourcing !

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OPT (2022)

OPT: Open Pre-trained Transformer Language Models

Susan Zhang*, Stephen Roller*, Naman Goyal*,
Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li,
Xi Victoria Lin, Todor Mihaylov, Myle Ott†, Sam Shleifer†, Kurt Shuster, Daniel Simig,
Punit Singh Koura, Anjali Sridhar, Tianlu Wang, Luke Zettlemoyer

Meta AI

{susanz,roller,naman}@fb.com

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Xi Victoria Lin, T … t Shuster, Daniel Simig,
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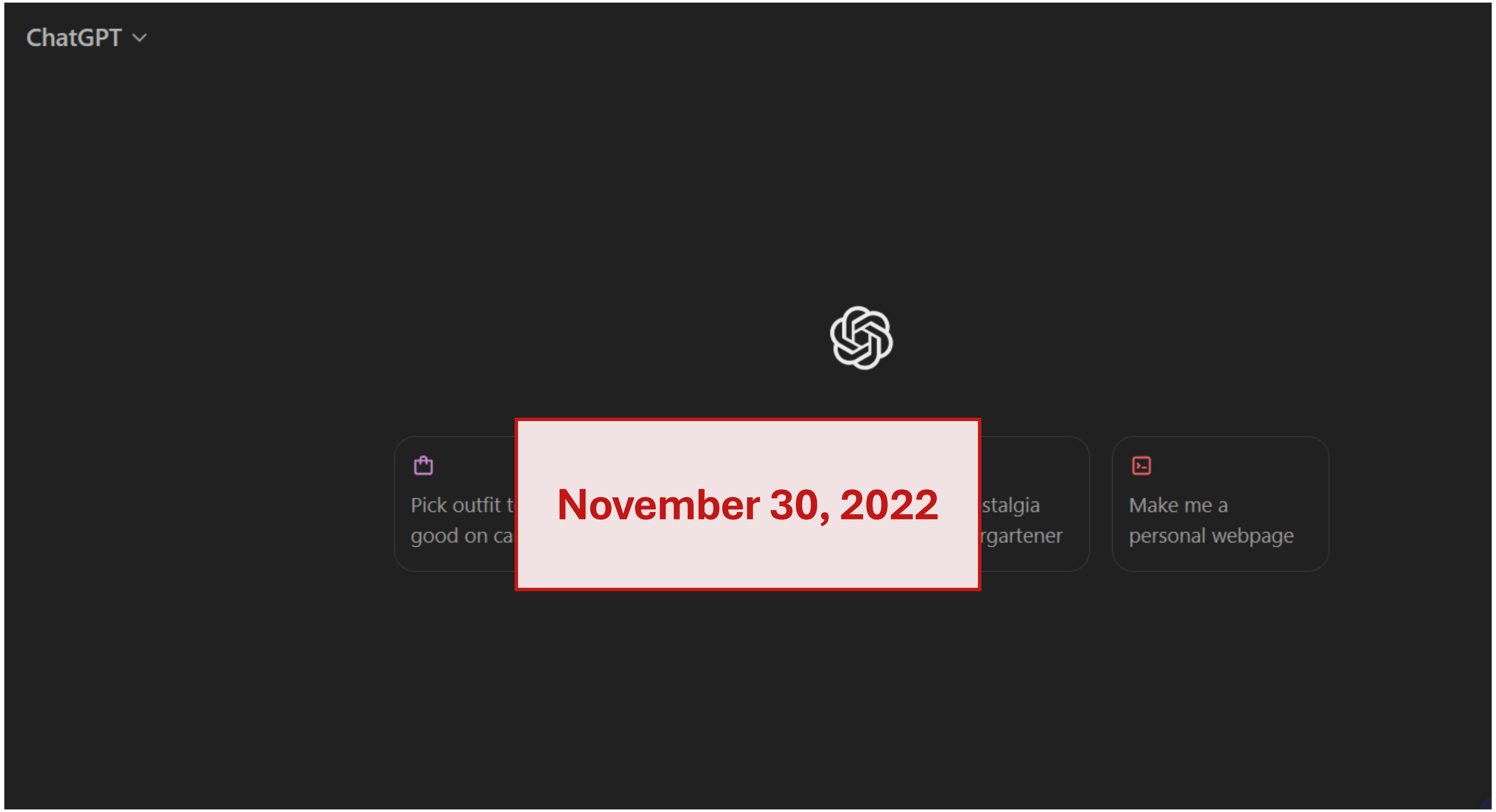
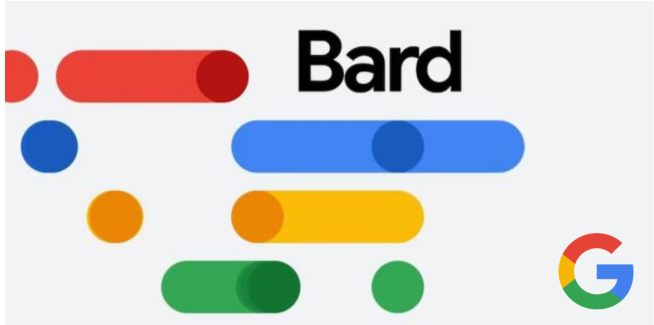
- A suite of decoder-only pre-trained transformers ranging from 125M to 175B parameters
- **Open-sourced !!!**

The ChatGPT Moment



November 30, 2022

2023: The Year of Rapid Pace



Feb, 2023: **Google** releases **Bard**

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Dec, 2023: **Google** releases **Gemini**

And now we are in 2024 seeing even more rapid advancements !

Gemma 2

GPT-4o

Llama 3
From Meta

{ Codestral }

Why Does This Course Exist?

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Why do we need a separate course on LLMs? What changes with the scale of LMs?

Content credits: https://stanford-cs324.github.io/winter2022/

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Why do we need a separate course on LLMs? What changes with the scale of LMs?

Emergence

Content credits: https://stanford-cs324.github.io/winter2022/

Why Does This Course Exist?

Why do we need a separate course on LLMs? What changes with the scale of LMs?

Emergence

Although the technical machineries are almost similar, ‘just scaling up’ these models results in new **emergent** behaviors, which lead to significantly different capabilities and societal impacts.

Content credits: https://stanford-cs324.github.io/winter2022/

Why Does This Course Exist?

LLMs show emergent capabilities, not observed previously in ‘small’ LMs.

Content credits: https://stanford-cs324.github.io/winter2022/

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LLMs show emergent capabilities, not observed previously in ‘small’ LMs.

- In-context learning: A **pre-trained language model** can be guided with **only prompts to perform different tasks (without separate task-specific fine-tuning)**.
  - In-context learning is an example of **emergent** behavior.

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LLMs are widely adopted in real-world.

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LLMs are widely adopted in real-world.

- **Research**: LLMs have transformed **NLP research** world, achieving state-of-the-art performance across a wide range of tasks such as sentiment classification, question answering, summarization, and machine translation.

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LLMs are widely adopted in real-world.

- **Research**: LLMs have transformed **NLP research** world, achieving state-of-the-art performance across a wide range of tasks such as sentiment classification, question answering, summarization, and machine translation.
- **Industry**: Here is a very incomplete list of some high profile large language models that are being used in **production systems**:
  - Google Search (BERT)
  - Facebook content moderation (XLM)
  - Microsoft's Azure OpenAI Service (GPT-3/3.5/4)

Content credits: https://stanford-cs324.github.io/winter2022/

Why Does This Course Exist?

With tremendous capabilities, LLMs' usage also carries various **risks**.

Content credits: https://stanford-cs324.github.io/winter2022/

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With tremendous capabilities, LLMs' usage also carries various **risks**.

- **Reliability & Disinformation:** LLMs often hallucinate – generate responses that *seem correct*, but are not factually correct.
  - Significant challenge for high-stakes applications like healthcare

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- **Social bias**: Most LLMs show performance disparities across demographic groups, and their predictions can enforce stereotypes.
  - P(**He** is a doctor) > P(**She** is a doctor.)
  - Training data contains inherent bias

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  - Trained on a huge amount of Internet data (e.g., Reddit), which inevitably contains offensive content
  - Challenge for applications such as writing assistants or chatbots

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  - Trained on a huge amount of Internet data (e.g., Reddit), which inevitably contains offensive content
  - Challenge for applications such as writing assistants or chatbots
- **Security**: LLMs are trained on a scrape of the public Internet - anyone can put up a website that can enter the training data.
  - An attacker can perform a **data poisoning** attack.

Content credits: https://stanford-cs324.github.io/winter2022/

We Will Cover Almost All of These in 5 Modules

Module-1: Basics

- A **refresher on the basics of NLP** required to understand and appreciate LLMs
- How did we end up in **Neural NLP**?
  - We will discuss the transition and the foundations of Neural NLP.
- The basics of **Language Modelling**
- Initial **Neural LMs**

Intro to NLP	Intro to Language Models (LMs)
Word Embeddings (Word2Vec, GloVE)	Neural LMs (CNN, RNN, Seq2Seq, Attention)

We Will Cover Almost All of These in 5 Modules

- Module-2: Architecture
  - Workings of **Vanilla Transformers**
  - Different **Transformer Variants**
    - How do their training strategies differ? How are Masked LMs (like, BERT) different from Auto-regressive LMs (like, GPT)?
  - **Response generation (Decoding) strategies**
  - What makes modern open-source LLMs like LLaMA & Mistral more effective over vanilla transformers?
    - An in-depth exploration of the **advanced attention mechanisms**
  - **Mixture-of-Experts**: an effective architectural choice in modern LLMs

Intro to Transformer	Decoder-only LM, Prefix LM, Decoding strategies
Encoder-only LM, Encoder-decoder LM	Advanced Attention
Mixture of Experts	

We Will Cover Almost All of These in 5 Modules

- Module-3: Learnability
  - **Scaling Laws**: how does performance vary with scale of LMs? When does 'emergence' kick in?
  - What makes modern LLMs so good in following user instructions?
  - What is **In-context Learning**? What are its various facets?
  - How are LLMs made to **generate responses preferred by humans**?
    - Does it remove toxicity in responses?
  - **Efficiency** is crucial in production systems.
    - How are smaller LMs made capable using pre-trained LLMs?
    - How are LLMs efficiently fine-tuned?
    - How are response generation latency of LLMs improved?

Scaling laws	Instruction fine-tuning
In-context learning	Alignment
Distillation and PEFT	Efficient/Constraint LM inference

We Will Cover Almost All of These in 5 Modules

- Module-4: User Acceptability
  - How can we make LLMs aware of certain relevant facts while generation?
  - Can LLMs operate in **multiple languages**?
  - Can LLMs reason?
  - Can **usage of external tools** help LLMs perform better?
  - Can LLMs handle **multiple modalities, like image**?
    - What changes are required in their architecture to do so?
  - How much long inputs can LLMs candle?
    - How can we **increase their context length**?
  - Can we **edit model components** to mitigate certain issues in LLMs?

Retrieval-Augmented Generation (RAG)	Multilingual LMs	Reasoning
Tool-augmented LMs	Vision Language Models	Handling long context
	Model editing	

We Will Cover Almost All of These in 5 Modules

- Module-5: Ethics and Miscellaneous
  - A discussion on **ethical issues** and **risks** of LLM usage
  - How are different emergent abilities in LLMs facilitated?
    - A peep into the internal workings of LLMs to understand the source of their capabilities
  - Can LMs based on alternate architecture match Transformer-based LLMs?
    - **State-Space Models (SSMs)**

Bias, toxicity and hallucination

Interpretability

Beyond Transformer: State Space Models

Suggestions (For Effective Learning)

- To understand the concepts clearly, experiment with the models (**Hugging Face** makes life easier).
- Smaller models (like, GPT2) can be run on **Google Colab** / **Kaggle**.
  - Even 7B models can be run with proper quantization.

Always **get your hands dirty !**

LLM Research is all about implementing and experimenting with your ideas.

Suggestions (For Effective Learning)

- To understand the concepts clearly, experiment with the models (**Hugging Face** makes life easier).
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Rule of thumb:

Never believe in any hypothesis until your experiments verify it !