Large Language Models

Introduction and Recent Advances

ELL881 · AIL821

Tanmoy Chakraborty
Associate Professor, IIT Delhi



Course Instructors



Tanmoy ChakrabortyIIT Delhi



Sourish Dasgupta DA-IICT



Yatin Nandwani IBM Research



Gaurav Pandey IBM Research



Dinesh Raghu IBM Research



Manish Gupta
Microsoft

Course TA



Anwoy ChatterjeePhD 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: Bharti-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 Q
- 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 GenAl 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.





- This is an <u>advanced graduate course</u> 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

Basics

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





Architecture Basics Intro to NLP Intro to Transformer Intro to Deep Learning Decoder-only LM, Prefix LM, Intro to Language Decoding Models (LMs) strategies Word Embeddings Encoder-only LM, (Word2Vec, Encoder-decoder GloVE) LM Neural LMs (CNN, Advanced RNN, Seq2Seq, Attention Attention) Mixture of Experts





Basics	Architecture	Learnability
 Intro to NLP Intro to Deep Learning Intro to Language Models (LMs) Word Embeddings (Word2Vec, GloVE) Neural LMs (CNN, RNN, Seq2Seq, Attention) 	 Intro to Transformer Decoder-only LM, Prefix LM, Decoding strategies Encoder-only LM, Encoder-decoder LM Advanced Attention Mixture of Experts 	 Scaling laws Instruction fine-tuning In-context learning Alignment Distillation and PEFT Efficient/Constraint LM inference





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Pre-requisites

- Excitement about language!
- Willingness to learn

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Mandatory	Desirable
Data Structures & AlgorithmsMachine LearningPython programming	NLPDeep learning



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This course will NOT cover:

- Details of NLP, Machine Learning and Deep Learning
- Coding practice
- Generative models for image/vision





Reading and Reference Materials

Books

- 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.

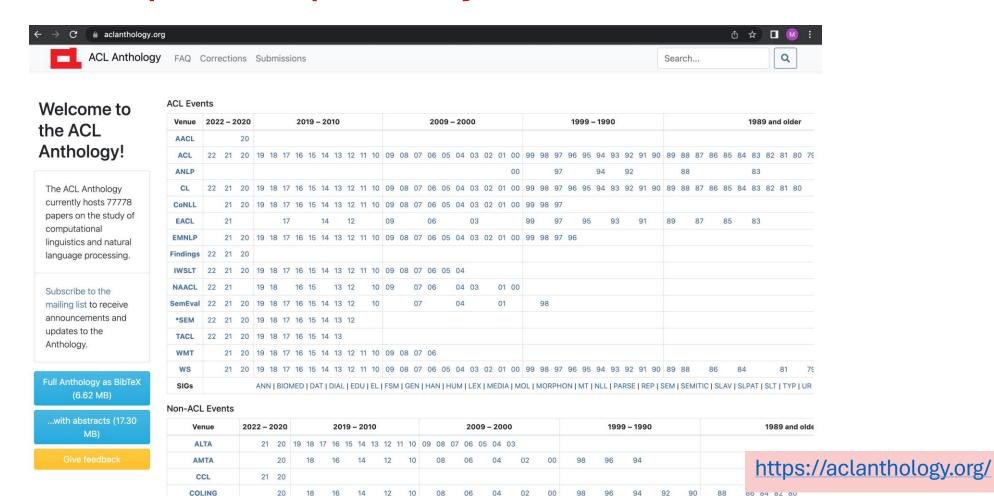
Conferences

ACL, EMNLP, NAACL, COLING, AAAI, IJCNLP, ICML, NeurIPS, ICLR, WWW, KDD, SIGIR, etc.





Research Papers Repository







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 lyyer 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, <u>CS 601.471/671: Self-supervised Models (jhu.edu)</u>
- WING.NUS Large Language Models, https://wing-nus.github.io/cs6101/
- And many more...





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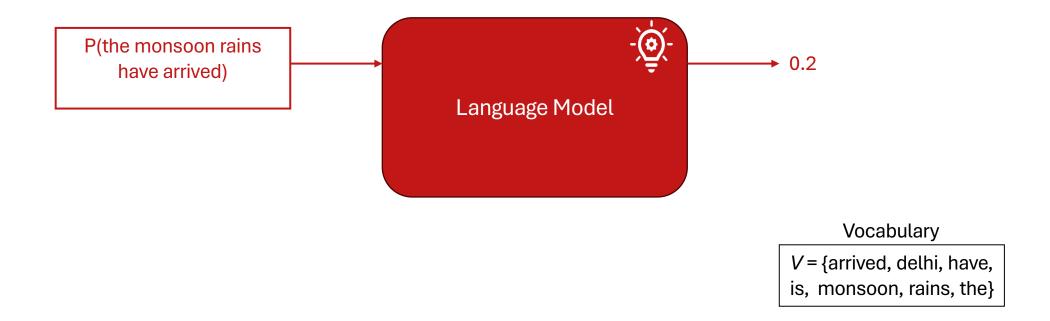
Vocabulary

V = {arrived, delhi, have,
is, monsoon, rains, the}





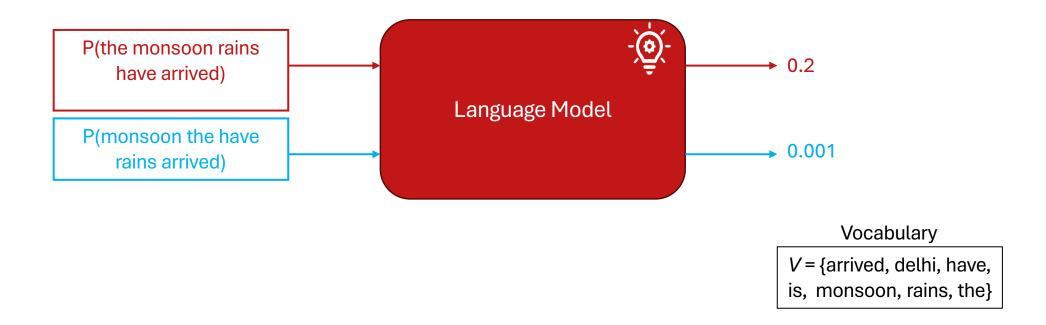
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Language Model gives the probability distribution over a sequence of tokens.







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

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

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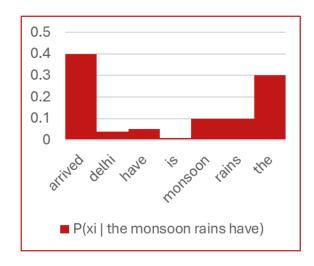
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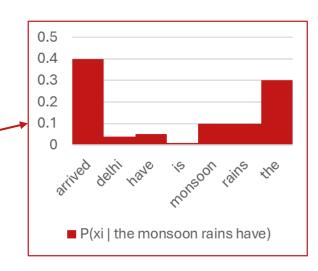
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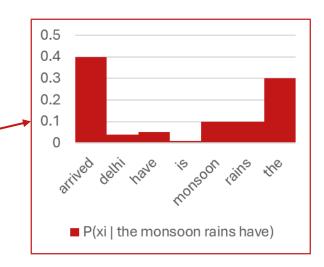
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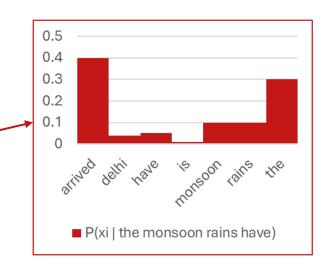
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Auto-regressive LMs calculate this distribution efficiently, e.g. using 'Deep' Neural Networks For generation, next token is sampled from this probability distribution

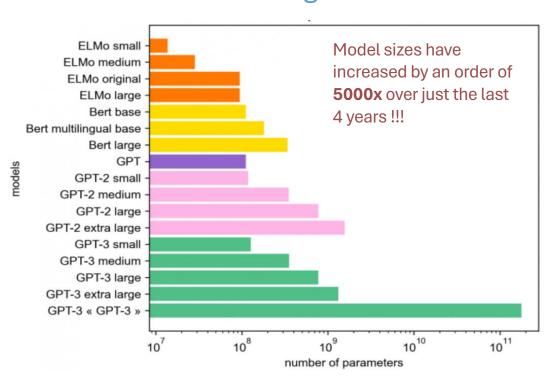
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'Large' Language Models

The 'Large' in Large Language Model refers to model's size in terms of parameters as well as the massive size of training dataset.



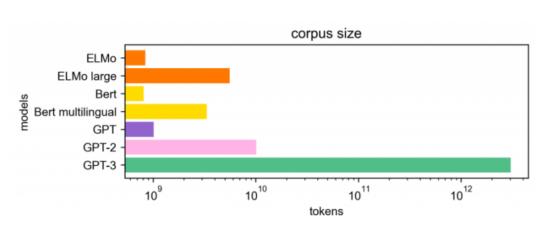


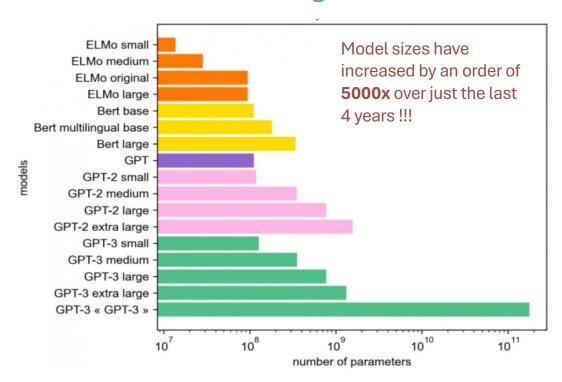
Image source: https://hellofuture.orange.com/en/the-gpt-3-language-model-revolution-or-evolution/

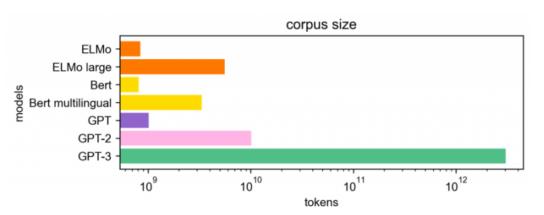




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Other recent models: PaLM (540B), OPT (175B), BLOOM (176B), Gemini-Ultra (1.56T), GPT-4 (1.76T)

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 Al Landscape

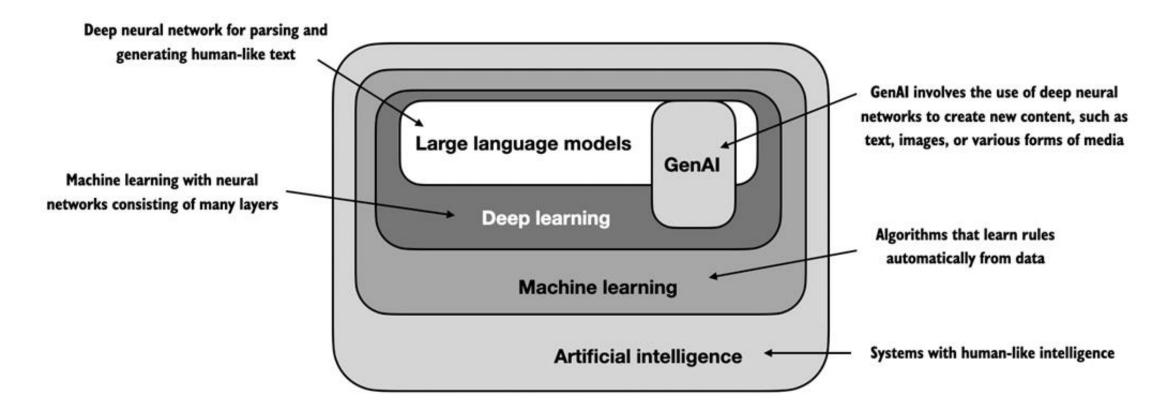
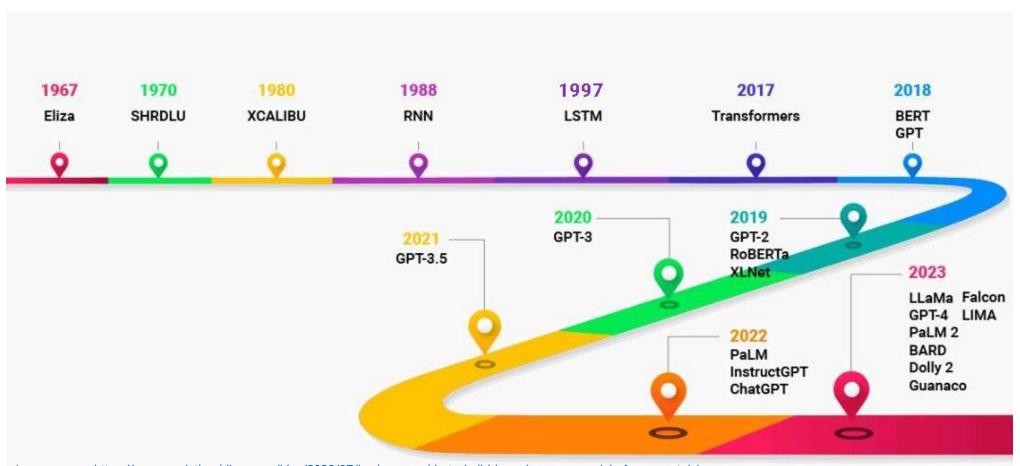


Image source: https://www.manning.com/books/build-a-large-language-model-from-scratch





Evolution of (L)LMs



We will discuss about many of them in this course!







Why does this course exist?

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





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Emergence



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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.





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- In-context learning: A pre-trained language model can be guided with only prompts to perform different tasks (without separate task-specific fine-tuning).
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- **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 OpenAl Service (GPT-3/3.5/4)



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





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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



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

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- **Toxicity**: LLMs can generate toxic/hateful content.
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- **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.







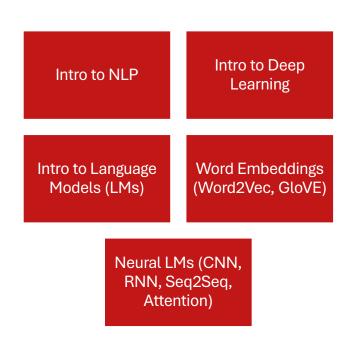
Module-1: Basics

- A refresher on the basics of NLP and DL required to understand and appreciate LLMs
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 - We will discuss the transition and the foundations of Neural NLP.
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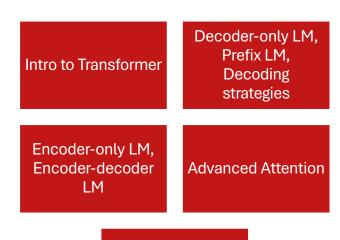


- Module-2: Architecture
 - Workings of Vanilla Transformers
 - Different Transformer Variants
 - How do their training strategies differ? How are Masked LMs (like, BERT)
 different from Auto-regressive LMs (like, GPT)?
 - Response generation (Decoding) strategies
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Mixture of Experts



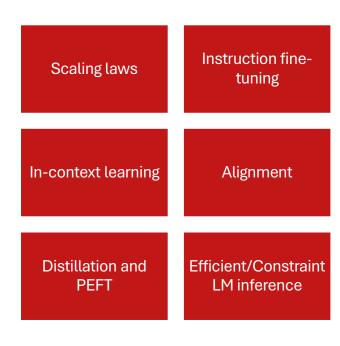


- Module-3: Learnability
 - Scaling Laws: how does performance vary with scale of LMs? When does 'emergence' kick in?
 - What makes modern LLMs so good in following user instructions?
 - What is In-context Learning? What are its various facets?
 - How are LLMs made to generate responses preferred by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





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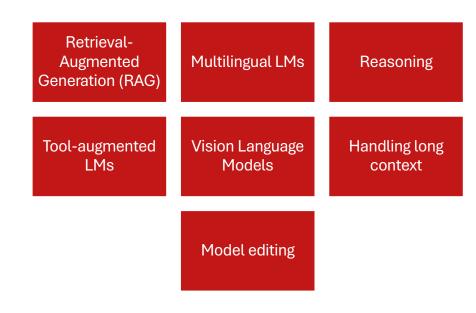


- Module-4: User Acceptability
 - How can we make LLMs aware of certain relevant facts while generation?
 - Can LLMs operate in multiple languages?
 - Can LLMs reason?
 - Can usage of external tools help LLMs perform better?
 - Can LLMs handle multiple modalities, like image?
 - What changes are required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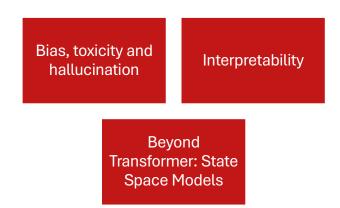


- Module-5: Ethics and Miscellaneous
 - A discussion on ethical issues and risks of LLM usage
 - How are different emergent abilities in LLMs facilitated?
 - A peep into the internal workings of LLMs to understand the source of their capabilities
 - Can LMs based on alternate architecture match Transformer-based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

Rule of thumb: Do not believe in any hypothesis until your experiments verify it!



