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Literature of Large-Language-models

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ABSTRACT: Recent years have seen a remarkable upsurge in the advancement of Large Language Model (LLM) systems beyond textual synthesis. In this regard, the success of LLMs has positively motivated a great deal of research work in this area. These works, in turn, include many aspects such as new architectures, new ways of training, increasing context lengths, fine-tuning, LLMs and robotics, datasets, benchmarking, and efficiency, among many others. Given the ever-increasing pace of technology in general and developments in LLM related research in particular, placing these advances in context has become quite difficult. In view of the constant and ever growing literature on LLM. It is also important that the research community is able to access brief but up-to-date summaries of the recent changes which have occurred within the field, Thank you. The purpose of the current article is to synthesize the available research on a variety of concepts associated with LLMs. In this treatise, we provide a detailed assessment of LLMs as well as background material on LLMs and frontier research topics on LLMs. This review article aims to not just provide a structured review but also a swift and an exhaustive collection of the pertinent information which researchers, and practitioners, would require in order to understand the scope of the literature available on the subject matter, and more importantly, on the existing gaps in order to initiate LLM research.

KEYWORDS: Large Language Models , Training , LLMs and robotics , LLM research .

I. INTRODUCTION

Huge models, like OpenAI's GPT and Google's PaLM, have reshaped various spaces in applications, from natural language processing and automation to content generation. The most promising application of LLMs is the writing of technical papers. Such models use enormous datasets and state-of-the-art deep learning techniques to demonstrate a good deal of potential for helping researchers and professionals draft, frame, and sharpen their technical documents.

That is, with LLMs, one would be able to speed up the whole process of paper development-from idea generation and literature review synthesis to wording for coherent parts of the paper and then readability and formatting. One more advantage that LLM's provide, though, is that they overcome writer's block, propose change recommendations, and ensure linguistic correctness, which is especially precious in very technical fields where correctness and clarity come first.

This literature review discusses the status of LLM applications to technical paper writing, canvassing a wide range of strengths and challenges that those models pose. It looks at existing research on using these models for parts of the writing process, productivity enhancement, and maintaining scientific input. It also discusses the limitations of LLMs regarding extremely specialized knowledge and the possibility of errors. It also analyzes ethical challenges of plagiarism and authorship.

II. BACKGROUND

2.1Tokenization

Tokenization is an important pre-processing step in LLM training that breaks the text into non-decomposing units called tokens. Tokens can be characters, subwords [60], symbols [61], or words, depending on the tokenization process. Wordpiece [62], byte pair encoding (BPE) [61], and unigramLM [60] are some of the most commonly used schemes in LLMs for tokenization. Readers are encouraged to refer to [63] for adetailed survey..

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2.2Encoding Positions

Parallel and independent processing of input sequences is how the transformer works. Additionally, it has recently been realized that positional information is not considered by the attention module in the transformer.To address this issue, positional encodings were introduced in transformer [64], where a positional embedding vectoris added to the token embedding. Variants of the positional embedding include absolute, relative, or learned positional encodings. Among relative encoding, Alibi and RoPE are the most prevalent positioning embeddings used in LLMs.

Alibi [65]: It subtracts a scalar bias from the attention score that increases with the distance between token positions. This favors using recent tokens for attention.

RoPE [66]: It rotates query and key representations at an angle proportional to the token absolute position in the input sequence, resulting in a relative positional encoding scheme which decays with the distance between the tokens.

2.3Attention in LLMs

Attention learns the weighting of input tokens based on relevance so that the model focuses more on important tokens.Attention in transformers [64] calculates query, key, and value mappings over input sequences. Attention score is obtained by multiplying the query with the key, and the resultant attention weights are used invalues. We discuss different types of attention mechanisms used in LLMs in the following sections.

Self-Attention [64]: Calculates attention by using queries, keys, and values from the same block, either an encoder or decoder.

Cross Attention: It is applied in encoder-decoder architectures, where encoder outputs are the queries, and key-value pairs come from the decoder.Sparse Attention [67]: Self-attention has O(n^2) time complexity which becomes infeasible for large sequences. To speedup the computation, sparse attention [67] iteratively calculates attention in sliding windows for speed gains.Flash Attention [68]: Memory access is the major bottleneck in calculating attention using GPUs. To speed up, flash Attention makes use of input tiling to decrease the number of memory reads/writes between the GPU HBM and the on-chip SRAM.

2.4Activation Function

The activation functions serve a crucial role in the curvefitting abilities of neural networks [69]. We discuss activation functions used in LLMs in this section. ReLU [70]: The Rectified linear unit (ReLU) is defined as:

$$\mathrm{ReLU}(x) = \max(0, x) \ldots\ldots (1)$$

GeLU [71]: The Gaussian Error Linear Unit (GeLU) is the combination of ReLU, dropout [72] and zoneout [73]. GLU variants [74]: The Gated Linear Unit [75] is a neural network layer that is an element-wise product ($\otimes$) of a linear transformation and a sigmoid transformed (σ) linear projection of the input given as:

$$\mathrm{GLU}(x, W, V, b, c) = (xW + b) \otimes \sigma(xV + c), \ldots\ldots (2)$$

where X is the input of layer and l, W, b, V and c are learned parameters. Other GLU variants [74] used in LLMs are:

$\mathrm{ReGLU}(x, W, V, b, c) = \max(0, xW + b)\otimes$,

$\mathrm{GEGLU}(x, W, V, b, c) = \mathrm{GELU}(xW + b) \otimes(xV + c)$,

$\mathrm{SwiGLU}(x, W, V, b, c, \beta) = S\ \mathrm{wish}\beta(xW + b) \otimes (xV + c)$.

2.5Layer Normalization

It pushes convergence to be even faster and is in fact integrated in transformers [64]. Besides LayerNorm [76] and RMSNorm [77], LLMs also contain pre-layer normalization [78], which it applies before MHA.

Pre-norm shows to provide stable training from constant in LLMs. DeepNorm [79] is another variant of normalization that fixes the problem with larger gradients pre-norm.

2.6Libraries

Some commonly used libraries for LLMs training are

Transformers [82]: The library provides access to various pretrained transformer models with APIs to train, fine-tune, infer, and develop custom models. DeepSpeed [36]: A library for scalable distributed training and inference of deep learning models.

Megatron-LM [80]: It provides GPU-optimized techniques for large-scale training of LLMs.

JAX [83]: A Python library for high-performance numerical computing and scaleable machine learning. It can differentiate native Python and NumPy functions and execute them on GPUs.

Colossal-AI [84]: A collection of components to write distributed deep learning models.

BMTrain [81]: A library to write efficient stand-alone LLMs training code.

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FastMoE [85]: Provides API to build mixture-of-experts (MoE) model in PyTorch.
MindSpore [86]: A deep learning training and inference framework extendable to mobile, edge, and cloud computing.
PyTorch [87]: A framework developed by Facebook AI Research lab (FAIR) to build deep learning models. The main features of PyTorch include a dynamic computation graph and a pythonic coding style.
Tensorflow [88]: A deep learning framework written by Google. The key features of TensorFlow are graph-based computation, eager execution, scalability, etc.
MXNet [89]: Apache MXNet is a deep learning framework with support to write programs in multiple languages, including, Python, C++, Scala, R, etc. It also provides support for dynamic and static computation graphs.

III. LARGE LANGUAGE MODELS

3.1Pre -Trained LLMs

we summarize some of the most famous and well-known pretrained LLMs that have led to groundbreaking discoveries, which significantly alter the course Scope of research and development in NLP. These LLMs have significantly improved performances in the domains of NLU and NLG. and are heavily fine-tuned for downstream tasks. In addition, We Moreover, identify key findings and insights of pre-trained LLMs in Table 1 and 2 that enhances their performance.

3.2Trained LLMs

Trained Large Language Models.
Large Language Models (LLMs) are sophisticated machine learning models designed to learn, generate, and manipulate human language. These models are "trained" on enormous amounts of text data from all over the world with the aim of predicting and generating the next word in a sequence, hence making them capable of doing a wide range of language-related tasks, including but not limited to: text generation, summarization, translation, question-answering, and more. The training process is typically an unsupervised process, in which the model essentially learns from patterns and structures that are inherent to the data rather than having program rules specific to a given task provided.

Overview: Training Process, Structure of Trained LLMs, and Some Key Models in the Field
1. Training Process of LLMs
Trillions of typical words in the training datasets used for LLMs. The reasoning for this type of training comes from the intuition of providing the model with a wide range of text from books, articles, websites, academic papers, code repositories, and all available textual data. Key steps in this process are the following:

Data Preprocessing: Unfiltered text data is first transformed and segmented into much smaller units called tokens, which could be words, subwords, or even characters. This way, the model will break down linguistic structure and contextual information on different levels of granularity.

Model Architecture: The most modern LLMs follow transformer-based architecture that relies on self-attention mechanisms in order to process relationship among so many words in one sentence irrespective of their position.

Objective Function: At training time, LLMs are optimized by minimizing the prediction error; in the language model example above, this often uses an objective function like cross-entropy loss. This calculates a comparison of the predicted word or token with respect to the actual word from a given dataset and the model can update its inner parameters through backpropagation.

Fine-tuning: Fine-tuning is a normal procedure after enormous pre-training on large corpora. LLMs can be fine-tuned on specific task-specific datasets such as technical writing, technical texts; healthcare applications, medical texts, etc.

2. Important Features of Trained LLMs
Contextual Understanding: The biggest strength of LLMs lies in their ability to understand context over very long passages of text. Unlike other traditional models that look at words only 'nearby,' transformers-the architecture behind most modern LLMs-capture relationships between words that are far apart in the text.

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Generative capabilities: LLMs trained can generate human-like text, making them good for content generation, summarization, and code generation. They can be applied for complex tasks like paraphrasing sentences, answering questions about topics, among others.

Transfer Learning: Following training, LLMs can be further fine-tuned to a whole new set of tasks with relatively minimal amount of additional training. This flexibility gives them the potential for applying to various domains, ranging from casual conversation to technical or scientific writing.

Multilingual Capacity: Most of the bigger LLMs are trained on multilingual corpora, enabling them to read as well as produce text in multiple languages, thus making them usable across global applications.

3. Popular Trained LLM Models

Of late, several LLMs have been widely recognized due to their scale, capabilities, and applications. Among those most renowned models are:

GPT-3 (Generative Pretrained Transformer 3): As developed by OpenAI, GPT-3 happens to be one of the most popular LLMs in existence, with 175 billion parameters. It uses its vast knowledge to generate coherent, contextually relevant text based on a wide variety of prompts. GPT-3 is versatile in handling anything, from casual conversation to technical writing and generating code.

GPT-4: It is an improvement of GPT-3, and hence better compared to its predecessor in all aspects while also able to take care of complex input with a more accurate response as well as capacity for better reasoning. It is better placed at understanding and creating scientific and technical content.

BERT: Bidirectional Encoder Representations from Transformers BERT is a pretraining approach on a large corpus, recently proposed by Google based on the transformer model. Its capability for both upstream and downstream directions of encoding input has made it more effectively applicable in tasks regarding the understanding of any text, including question answering, sentiment analysis, and named entity recognition.

T5: The Google's people also developed T5, which treats all tasks as a "text-to-text" problem, where both the input and the output are text. It is a unified approach that makes T5 a very adaptable model that can adapt to any task that lies in NLP-in this case, summarization, translation, and question answering.

One other model of Google, PaLM is actually a hugely scaled-up transformer that balances an unusually high level of performance to a broad range of tasks while keeping state-of-the-art accuracy. In fact, it is supposed to be multilingually efficient and has been used to push the boundaries of performance in both research and commercial applications.

Codex: Developed by OpenAI, it is based on GPT-3. Fine-tuned for code generation, the Codex can also understand code and generate small code snippets as well as debug code. It's integrated in GitHub Copilot for the developers.

LaMDA (Language Model for Dialogue Applications): This model was developed by Google to be able to converse effectively and naturally on almost any topic. It is designed, therefore, to understand and generate human-like dialogue, making it suitable for conversational AI systems.

4. Applications of Trained LLMs

Scientific and Technical Writing: LLM may help researchers draft, refine, and structure technical papers. LLM generates content based on abstracts or summaries. It also proposes improvements with the intent of better clarity and coherence.

Automated Code Generation: tools like GitHub Copilot utilize LLMs, Codex, for instance, to aid developers with the labor of code generation while getting them to write or complete code much more speedily by suggesting possibilities, debugging assistance, and actual code generation.

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This would mean that such trained LLMs could respond to user queries with contextual accuracy with the efficiency of the customer service bot, educational applications, and other automated help desks.

Content Creation: LLMs can create purposeful, well-targeted marketing materials as well as relevant social media posts, saving the time and effort taken by content creators.

Such an LLM like T5 and GPT 4 can translate the text from one language to another or paraphrase a long document, preserving the meaning and context.

5. Challenges and Limitations
Trained LLMs notwithstanding all their ability, they also do not come without limitations as:

Bias and Ethical Concerns: The risk with LLMs is that since the model learns from huge datasets, it can possibly reproduce the wrong things it was trained on or amplify negative biases in content. Models can be damaging when used for something like hiring decisions or when giving legal advice or even in health services.

Data and Privacy Concerns: Most of the data on which LLMs are trained is free for access in the public domain, thereby often raising concerns about individuals' private information and the possible generation by models of sensitive information in the process.

Interpretability and Transparency: The biggest LLMs have been considered "black-box" models, whereby their approach to arriving at any particular output cannot be made easily understood. This lack of transparency has already proven to be a barrier in applications where accountability and interpretability are critical.

Resource Intensity:Training and fine-tuning of large LLMs are computationally resource intensive and energy-expensive, both of which have a cost and an environmental impact.

3.3Architectures of some models
Exploration of new architectures in LLM is crucial with an increase in the requirement for higher linguistic processing .The form LLM will take depends on various factors such as the application in which the model is intended, amount of computational resource available and more generally on the type of language processing that the model is designed to perform.
An open source LLM gives a developer much more flexibility and control as they can adjust their model to suit specific requirements and resource limitations by fine-tuning.
The transformer architecture widely gets adopted in LLMs like GPT, BERT, and RAG.
There also exist other architectures of LLMs specifically designed for the enterprise applications, such as Falcon, OPT, that put forward special features in terms of design to meet the various particular use cases.

LLM architecture explained
The overall architecture of LLMs comprises multiple layers, encompassing feedforward layers, embedding layers, and attention layers.
These layers collaborate to process embedded text and generate predictions, emphasizing the dynamic interplay between design objectives and computational capabilities.

LLM architecture diagram
Here’s the emerging architecture for LLM applications

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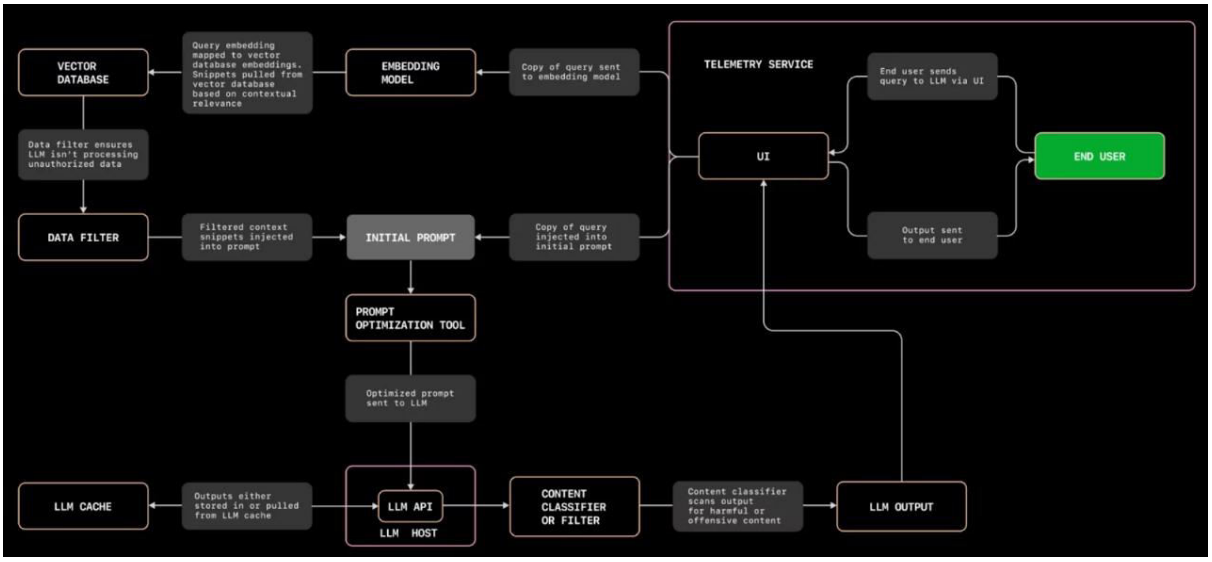
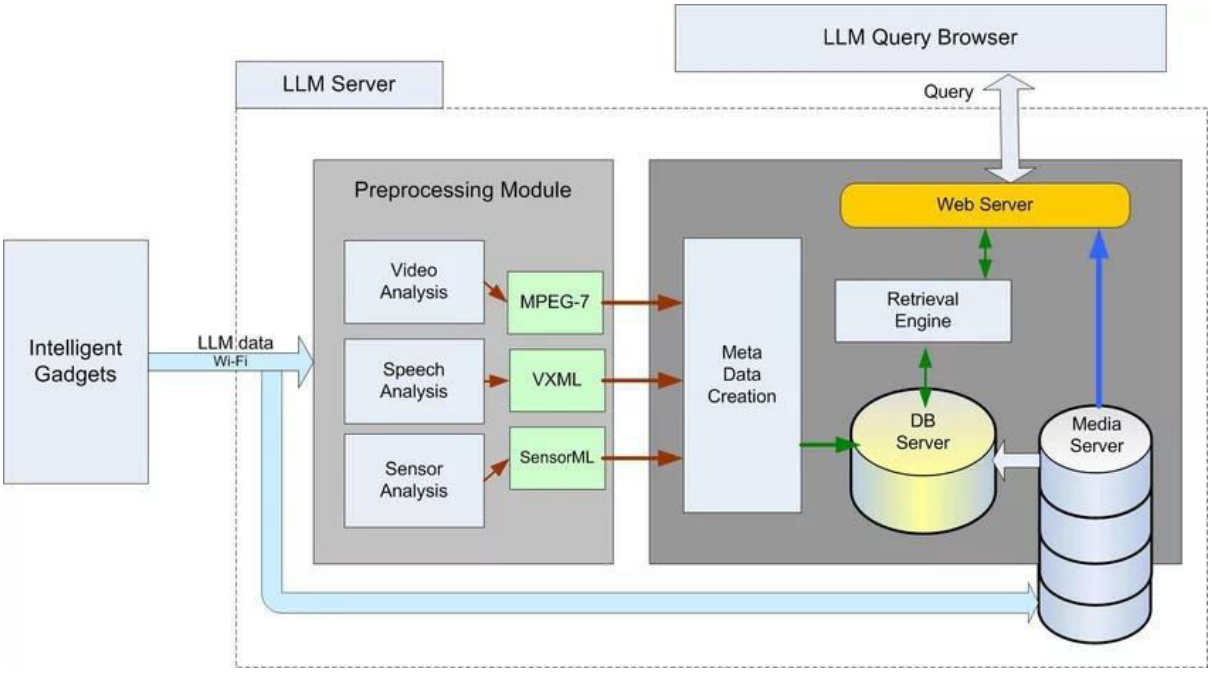


Here's another LLM system server architecture:



Transformer architecture

The Transformer deep learning architecture is a revolutionary milestone in language processing, particularly in the domain of Large Language Models (LLMs).

A transformer model, introduced in 2017 by Ashish Vaswani and teams from Google Brain and the University of Toronto, is a neural network that captures context and meaning by analyzing relationships within sequential data, such as the words in a sentence.

Transformer models discern nuanced connections among even distant elements in a sequence using evolving mathematical techniques known as attention or self-attention.

This innovative architecture has found implementation in prominent deep learning frameworks like TensorFlow and Hugging Face's Transformers library, solidifying its impact on the landscape of natural language processing.

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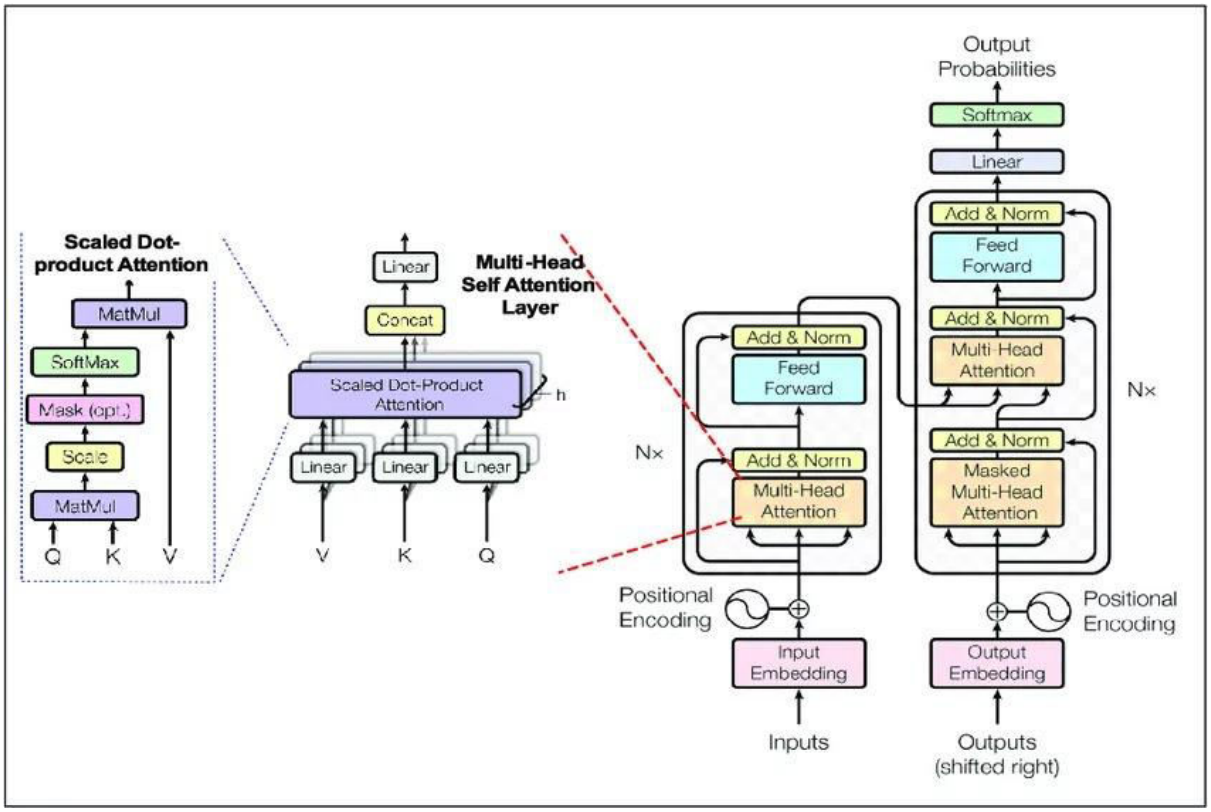
Transformer models

Various transformer models, such as GPT, BERT, BART, and T5, encompass the language processing.

The transformer architecture, renowned as the foremost Large Language Model (LLM) framework, illustrates its versatility and prominence in advancing the capabilities of language-centric AI systems.



Transformer Explained

The core idea behind how transformer models work can be broken down into several key steps:

Input Embeddings: The initial step in transformer models involves converting the input sentence into numerical embeddings, representing the semantic meaning of tokens within the sequence. These embeddings can either be learned during training or obtained from pre-existing word embeddings for word sequences.

Positional Encoding: To understand the sequential order of words, the input undergoes positional encoding. This process encodes the input based on its position in the sequence, enabling the model to comprehend the contextual relationships between words.

Self-Attention: Transformer models employ a crucial mechanism known as self-attention, allowing the model to weigh the significance of individual words in the input sequence. This attention mechanism enables the model to focus on relevant words and capture intricate relationships between them.

Feed-Forward Neural Networks: Following the self-attention phase, the model utilizes feed-forward neural networks to enhance the information contained in the representations. This step contributes further insights to the model's understanding of the input sequence.

Output Layer: The final output is generated based on the transformed representations obtained through the preceding steps, reflecting the model's interpretation of the input sentence.

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3.4Applications of Trained LLMs

Large language models for downstream applications It is apparent that this trend toward using large language models for the wide range of downstream tasks is going quite trendy among AI research communities and the industries, where a new, promising application is discovered and explored each day. Having the capability to learn and generate text almost similar to human performance, LLMs have goingly found meaningful applications in various fields. This cap-ter provides an overview of applications of LLM in medicine, education, science, mathematics, law, finance, robotics, and Coding. Although each of the above domains poses unique challenges, LLMs provide opportunities for significant contributions to these domains by virtue of their generalizability

1. Content Generation

The main domain to which LLMs can be applied is content generation. They are used heavily in marketing, entertainment, and journalism.

Article and Blog Writing: LLMs can write coherent informative text based on topic prompts for articles, blog posts, and summaries of news. This is useful for the content generator who needs ideas and the first draft instantly.

Creative writing: The LLMs can assist creative writers in generating the plot, develop the character, even compose poetry and short stories. Use brainstorming by creative professionals as a means to defeat writer's block and explore new writing styles.

Social media posts: LLMs can produce engaging and contextually relevant content for social media platforms such as Twitter, Facebook, or LinkedIn. They can be tailored towards brand voice, which helps marketers and business keep a consistent online presence.

2. Technical and Scientific Writing

LLMs have given excellent demonstrations in fine-tuning technical writing and fine-tuning academic paper writing.

Automated draft for a paper: LLMs can help a scientist draft parts of scientific papers. Among them are introductions, literature reviews, and even conclusions. It is possible for these models to summarize the related work, generate hypotheses, and give suggestions for the setups of experiments based on input data.

In the technical fields like software development, OpenAI's Codex LLM can produce code from natural language descriptions. This keeps users able to rapidly create software and free up repetitive coding work while maintaining good documentation of codebases.

Data Analysis and Summarization Trained LLMs could be used to make sense of data coming from research, turning summaries or insights from scientific articles, reports, or datasets. This would be very useful in bioinformatics, physics, and social sciences since data are abundant in such fields.

3. Customer Support and Chatbots

LLMs have been applied as the basis of building intelligent conversational agents that may be able to interact with end-users naturally as in context-sensitive dialogues.

Customer Service: LLMs enable virtual assistants and chatbots to answer customer questions, troubleshoot, and provide support. All of these systems can respond to questions, solve problems, and forward the more complex issues to the humans for further handling.

Availability 24/7: Since LLM-powered systems can operate continuously without any pause, they are very beneficial for businesses that need to have customers supported at all times, offering fast, scalable solutions without human intervention.

Personal Assistants: Virtual assistants like Siri from the App company, Alexa of Amazon, and Google Assistant all function on the basis of LLM. They remind users of an event, answer their questions, or make suggestions.

4. Language Translation

LLMs have greatly improved the machine translation systems to be nearer to the truth and subtler.

Multilingual Support: Models like Google Translate have revolutionized the way we communicate when language is a barrier. With such training, models can translate text into many languages and deal with complex nuances and idiomatic expressions.

Real-Time Translation: LLMs can be used for real-time translation in applications like video conferencing or customer support, where language won't be a problem in multi-national settings.

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5. Sentiment Analysis and Opinion Mining
LLMs are applied in the comprehension of public opinions and customer opinion analysis from feedback, social media, and product reviews.
Brand Monitoring: Corporations utilize sentiment analysis to understand the prevailing view of the general public regarding its products or services or its brand reputation. LLMs analyze large amounts of texts to identify whether the customers' sentiment is positive, negative, or neutral.
Market Research: LLMs can gather and analyze customer reviews, surveys, and social media updates to unveil trends in consumer behavior and preference and input into the development of a product or marketing strategy.

6. Healthcare and Life Sciences
LLMs have increasingly found their way into healthcare with the help they provide with medical research, diagnosis, and patient communications.
Medical Research: LLMs may facilitate researchers to find relevant study papers, summarize results, and provide insights into areas that require further investigation. They can even derive hypotheses for research and conduct experiments as guided by previous work in the medical literature.
Clinical Decision Support: LLMs are applied in clinical decision support systems to support healthcare providers in disease diagnosis, treatment recommendations, and care management through analysis of medical records, lab findings, and clinical notes.
Patient Interface: LLMs can provide virtual health assistants the power to respond to patient inquiries or arrange an appointment. It can even provide mental health services by using conversational agents, which can make such health systems reach more.

7. Education and E-Learning
LLMs are used for augmenting learning experiences, automating some teaching jobs, and providing tailor-fit learning experiences.
Automated Tutoring: Depending on the subject, whether it is mathematics, science, or any other language-based subject, LLMs can provide some form of personalized tutoring; they can find out exactly what level a learner is at and offer perfectly tailored explanations and examples to reinforce learning for that individual.
Content Generation: LLMs can generate textbooks, study guides, and much more, cutting down the content generation process for educators and publishers.
Grading and Assessment: Several LLMs can be used to automate the grading process by checking essays and other assignments, giving feedback, and even suggesting how to improve. Thus, educators can save a lot of time and be more productive.

8. Legal and Compliance
LLMs are also transforming the legal industry by automating tasks such as reviewing documents, contracts, and regulatory compliance.
Some illustrations of how LLM may help legal professionals are as follows.
Contract Analysis: An LLM would be able to read contracts, outline the most critical clauses that could lead to potential risks or ambiguity. This would have a phenomenal saving in terms of the time spent upon manual contract review and its accuracy.
Legal Research: One significant feature of LLM would be to search through an enormous body of law documents, case laws, and statutes to find right precedents within no time.
Compliance. LLMs are applied in the processing of company documents to scan for compliance. Such a scan can be made on contracts, financial reports, and policy documentation to check for legal conformity and compliance with industry standards.

9. Financial Sector
In finance, LLMs are used in automated tasks, enhanced decision-making, and improved customer servicing.
Financial advisory: LLMs can assist in providing guidance to financial advisors through insights based on market data, economic reports, and financial trends. They can generate investment recommendations tailored to an individual's financial goals and risk tolerance.

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Fraud detection: LLMs can be trained to analyze transaction data to find patterns of suspicious activity. In this way, the LLMs can then process large volumes of transactional text and behavioral data for identifying patterns and expressions of fraudulent transactions in real-time.
Market Sentiment Analysis. LLMs will analyze news articles, social media, and financial reports in trading and investment to measure market sentiment for individual traders or investors to inform their trading and investing decisions.

10. Cybersecurity
LLMs are used in cybersecurity with anomaly detection, threat analysis, and automated incident response as its core functions.
Cyber Threat Hunting: Inferring big amounts of data within logs, network traffic, and communication channels with an objective of discovery of the possible cyber threats in the form of phishing attempts, malware, or hacking activities.
Automated Incident Response : Trained LLMs can automate a lot of responses to security events such as creating predefined actions in response to detected threats, which helps in quick response and much better risk mitigation.

11. Personalized Recommendations
LLMs are highly utilized in recommendation systems; they can be seen in retail, entertainment, and online applications.
Product-Based Recommendations: From e-commerce, LLMs rate the behavior of users, reviews, and preferences in recommending products to a person that fits his tastes or needs.
Content-Based Recommendation: For example, streaming services like Netflix, YouTube, and Spotify utilize LLMs for movie, video, or music recommendations by understanding the users' preference and other descriptors of content descriptions, genres, and viewing patterns

IV. CONCLUSION

This article has comprehensively surveyed the development of LLMs. It contributes to summarizing significant findings of LLMs in existing literature and also gives a detailed analysis of design aspects, including architectures, datasets, and training pipelines. We identified key architectural components and training strategies used by various LLMs. These are presented as summaries and discussions throughout the article. In addition, we have discussed the performance differences of LLMs in zero-shot

and few-shot settings, probed into the effect of fine-tuning and compared the models and architectures trained under supervised and generalized conditions and encoder versus decoder versus encoder-decoder. This report also encompasses a detailed overview of multi-modal LLM, retrieval augmented LLM, LLMs powered agents, efficient LLM, dataset, evaluation, applications, and challenges. The paper will be useful for researchers as it will help them gain insight into the recent work on LLM and some fundamental concepts and details to make better LLMs.

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