Language Model Evolution : GPT and Impact Beyond

Sandeep Bhattacharjee [1*]

Abstract

Language models are considered a way of machine level of understanding and predicting human languages as a part of human communication relevant to the context. The present research paper tries to understand the growth of such language models popularly known as GPT or Generative Pre-trained Transformer. It tries to understand the meaning, growth, working of model, and some of the applications where GPT is being used. Several applications on business, website development, and conversational applications are now being powered by GPT with tremendous potential for future convergence. Artificial Intelligence and sub-domains. This research paper can be very useful for academicians, researchers, and professionals who handle business and information technology applications.

Keywords : **Context, predictive, text, trained, transformer**

I. INTRODUCTION

A. History

The for-profit OpenAI LP and its non-profit parent firm, OpenAI Inc. make up the American Artificial Intelligence (AI) research facility known as OpenAI. The company performs AI research with the declared intention of advancing and creating benign AI in a way that benefits all human beings. Elon Musk, Sam Altman, and others formed the group in San Francisco at the end of 2015, with a US $1 billion commitment in total. In February 2018, Musk resigned from the board but continued to give money. Microsoft and Matthew Brown Companies invested US $1 billion in OpenAI LP in 2019. The Pioneer Building in San Francisco's Mission District serves as the home office for OpenAI.

B. General Understanding of GPT Model

GPT stands for Generative Pre-trained Transformer Machines that predict words that are language models. It is usually being trained on a vast amount of text, so when it encounters new text, it suggests potential next words. It grows more inventive the more text you train it with. Typically, language models are trained to do a single task, such as text production, summarization, categorization, etc. Input technology known as predictive text makes it easier to type on a device by recommending words the user might want to enter in a text field. The context of the message's other words and the first few letters written are used to make predictions [1].

II. TYPES OF GPT

The different types of GPT are described in this setion.

A. Transformers

A transformer models input using an encoder stack and output using a decoder stack (using input data from the encoder side [2].

B. GPT-2

In some cases when we don't have input, we just want to

Manuscript Received : December 20, 2022; Revised : January 12, 2023 ; Accepted : January 16, 2023. Date of Publication : February 5, 2023.

S. Bhattacharjee [1*], *Assistant Professor,* Amity School of Business, Amity University Kolkata, Major Arterial Road (South-East), AA II, Newtown, Kolkata, West Bengal - 700 135. Email : sandeepbitmba@gmail.com ;
ORCID iD : https://orcid.org/0000-0002-6686-3947

DOI : https://doi.org/10.17010/ijcs/2023/v8/i1/172680

model the “next word”, we can get rid of the Encoder side of a transformer and output “next word” one by one. This gives us GPT [2].

C. BERT

The decoder of the transformer provides us Bidirectional Encoder Representations from Transformers (BERT) which may indeed not be necessary if we only want to train a language model for the input for other tasks [2].

D. GPT-3

A neural network machine learning model that has been trained using data from internet sources is known as GPT-3, or the third generation Generative Pre-trained Transformer, which can produce any kind of text. It was created by Open AI and just needs a small amount of text as input to produce vast volumes of intelligently generated text [2].

The deep learning neural network in GPT-3 is a model that uses more than 175 billion machine learning parameters. In fact, Microsoft's Turing NLG model, which consists of 10 billion parameters was the largest trained language model preceding the evolution of GPT-3. The largest neural network ever created as of early 2021 is GPT-3. Because of this, GPT-3 outperforms all previous models in terms of producing text that appears to have been produced by a human. With just a modest quantity of text input, GPT-3 has been deployed to generate vast volumes of high-quality content including articles, poems, stories, news reports, and dialogue [2].

III. LITERATURE REVIEW

In their study, Thompson and Spanuth [3] made the case that current technological and economic factors are pushing computing in the opposite direction, leading to fewer general-purpose and more specialized computer processors. The slowing of Moore's Law and the success of Deep Learning algorithms have sped up this trend. This trend towards specialization poses the risk of fracturing computers into "fast lane" applications that benefit from strong tailored chips and "slow lane" applications that are constrained to employing general purpose chips that slow down. As per Floridi and Chiriatti [4], GPT-3 does not behave in a manner that is inconsistent with its design and that any interpretation that GPT-3 heralds the development of a generic kind of Artificial Intelligence is purely science fiction based on lack of knowledge. The researchers mention in the end by highlighting some of the key ramifications of the industrialization of cheap, automated, and cheap production of good, semantic artifacts. Knowledge-based visual question answering (VQA) carried out by Yang, Gan, Wang, Hu, Lu, Liu, and Wang [5] involves responding to inquiries that call for outside knowledge that is not depicted in the image. Existing techniques first retrieve information from outside sources before reasoning about the information that was chosen, the input image, and the query to predict the response.

Research by Dehouche [6] mentions the year 2020 which witnessed the development of the most potent natural language processing (NLP) system to date, GPT-3 (Generative Pre-trained Transformer-3) developed by Silicon Valley research company OpenAI. Examples of the Dehouche’s original content created with GPT-3 were provided in this work published in the same year. Some of them included some GPT-3 skills to understand natural language prompts and generated compelling content in the form of output. These outputs were applied to some very important issues with the intellectual property of such content and the potential for copying by using GPT-3. The intention was to observe a sense of urgency and present delay on the part of the academic community in addressing these questions. Peter Gärdenfors' semantic geometry offers a way of thinking about the dimensionality of mental space, the diversity of phenomena in the environment, and how the mind mirrors the outside world, according to Benzon's discussion in 2020 [7]. However, the absence of a sensory motor system that has evolved over millions of years limits artificial systems with some built-in restrictions. The understanding of the learning capabilities was also studied in subsequent research. According to Liu, Shen, Zhang, Dolan, Carin, and Chen [8], GPT-3 research had garnered a lot of interest because of its exceptional performance on a variety of NLP tasks, particularly with its potent and adaptable in-context few-shot learning capabilities. Despite its success, it was discovered that the selection of in-context instances has a significant impact on the empirical outcomes of GPT-3. Furthermore, it has been found that sentence encoders that have been improved on datasets and are connected to particular tasks that produce even more beneficial retrieval outcomes. Some of these tasks were table-to-text generation (41.9% on the ToTTo dataset) and open-domain question answering (45.5% on the NQ dataset) where notable improvements were seen.

According to Klinger, Mateos-Garcia, and Stathoulopoulos [9], locations that combine linked research and industrial activity are more likely to be where competitive DL (Deep Learning) clusters can be established. This might be because of the ease with which GPT developers and adopters in close proximity can work together and share expertise, solving coordination issues in GPT deployment. After adjusting for other explanatory variables, their study also found a Chinese comparative advantage in Deep learning (DL), presumably highlighting the significance of data access and encouraging policies for the successful development of this sophisticated, "omni-use" technology. A fresh piece of text that is relevant to the situation is automatically generated by GPT-3 in response to any text that is entered into a computer. The GPT-3 is not limited to writing in human languages; it can write anything with a text structure. Moreover, it is proficient in terms of automatically generating computer codes along with written summaries. Another task-oriented dialogue system, UBAR, which represented the task-oriented dialogues on a dialogue session level, was presented in a study by Yang, Li, and Quan [10]. The massive pre-trained unidirectional language model GPT-2 is specifically tuned to the sequence of the complete dialogue session, which is made up of user utterance, belief state, database result, system act, and system response of each dialogue turn, in order to acquire UBAR.

Furthermore, the introduction of Transformer models like the GPT-2 represents a paradigm shift and a huge potential for researchers in the patent field, according to Lee and Hsiang [11]. They used a span-based methodology to show how the text generating capabilities offered by the GPT-2 model could be used to complement invention. They also published both of their optimized 355M patent-specific model and the executable code. On GitHub, hundreds of patent claims have also been released as a part of study data. The best GPT recovers 64% (P@1) of world knowledge, according to Liu, Shen, Zhang, Dolan, Carin, and Chen [8], the knowledge probing (LAMA) benchmark, without the need of any additional test-day text time, which substantially improves the previous best by 20+ percentage points.

According to Ham, Lee, Jang, and Kim [12], the goal-oriented dialogue system needs to be improved for monitoring the dialogue flow and having productive conversations in a variety of contexts in order to achieve the user goal. A pipelined modular design with separately optimized modules is the conventional method for creating such a dialogue system. It includes an end-to-end neural architecture for dialogue systems in this study that takes on both of the aforementioned issues. Our dialogue system placed first in the end-to-end multi-domain conversation system job in the 8th dialogue system evaluation with a success rate of 68.32%, a language understanding score of 4.149, and a response appropriateness score of 4.287. The task incorporated carefully examining the text forms that can possibly best represent the visual information and how in-context samples can be better picked and utilized to create tools for further improve performance. GPT-3's first application to multimodal activities was unlocked by PICa which outperforms the supervised state of the art on the OK-VQA dataset by an absolute +8.6 points with just 16 examples.

This could be performed by an end-to-end neural architecture for dialogue systems which was placed first in the end-to-end multi-domain conversation system job in the 8^{th} dialogue system evaluation with a success rate of 68.32%, a language understanding score of 4.149, and a response appropriateness score of 4.287. In their 2020 study, Elkins and Chun [13] used structured grammar systems, small-scale statistical models, and extensive sets of heuristic rules to study the field of natural language creation. This earlier technology was fairly constrained and fragile as it could only communicate with people about themes that were specifically defined or remix language into word salad poems. GPT-3 is just one example of how very large-scale statistical language models have significantly advanced the field recently. Without explicit programming or rules, it can be capable of internalizing linguistic rules. GPT-3 can learn language by repeated exposure, albeit on a much bigger scale than a human infant would. Without clear standards, it can occasionally struggle with even the most basic linguistic tasks, yet it can also succeed at more challenging ones like copying authors or waxing lyrical.

Klein and Nabi [14] discussed the goal of automatic question generation which creates questions from context with the responses serving as sub-spans of the paragraph in question. While the majority of solutions primarily use heuristic principles to generate questions, neural network approaches have also been developed to support such relativity. A self-attention version had been developed using the neural network version to generate possibilities of questions and more probabilistic responses. The architecture generated from collaboration was able to enhance both tasks and perform especially well in the semi-supervised environment. The findings also point to a concrete and comparatively thin pipeline that makes question generation easier in the small-data threshold. A paradigm change in NLP research has occurred as a result of the recent success of zero- and few-shot prompting with models like the GPT-3 during a research conducted by Goyal, Li, and Durrett [15]. This study examined its effects on text summarizing with a particular emphasis on the traditional benchmark task of news summarization.

By evaluating GPT-3, McGuffie and Newhouse [16] built on the earlier research over the possibility of abuse of generative language models. During this research, GPT-3 significantly outperformed its predecessor GPT-2 in producing texts that are typical of various varieties such as extremist narrative, social interaction structures, and extreme beliefs. The prowess of GPT-3s was also observed in producing text that faithfully imitates interactive, educational, and persuasive materials that may be used to radicalize people towards violent far-right extremist views and practices. Abstract Meaning Representations are extensive sentence-level semantic graphs that Mager, Astudillo, Naseem, Sultan, Lee, Florian, and Roukos examined Abstract Meaning Representations [17]. The majority of previous methods for producing text from Abstract Meaning Representations have concentrated on training sequence-to-sequence or graph-to-sequence models exclusively on annotated Abstract Meaning Representations data. On the English LDC2017T10 dataset, new experimental results demonstrated that these Abstract Meaning Representations models outshine all prior methods including the more recent use of transformer structures. Human assessment tests in addition to the common evaluation metrics could be provided to support the effectiveness of our strategy.

Although English has benefited greatly from large generative language models, other languages have lagged behind, in part because of data and computational constraints, as studied by Vries and Nissim [18]. A new technique was developed that could solve these issues by converting current pre-trained models to new languages. This technique led to the reduction of the amount of training required and also prevented GPT-2 from forgetting what it learnt during adaption. Relearned lexical embeddings in English GPT-2 models could produce precise sentences in Italian and Dutch. These statements were evaluated on par with those produced by other GPT-2 models that had been fully trained from start, despite the fact that, on an average, some humans can still tell that they are fake.

Liao, Wang, Liu, and Jiang [19] offered a straightforward yet powerful strategy for training a generative pre-trained language model to produce high-quality classical Chinese poetry (GPT). This approach used a straightforward GPT model with no additional brain components or rules created by humans. This was the first time GPT was used to create a system for generating poetry. An online short demonstration programme on WeChat was also included in the publication to demonstrate the generation potential of the suggested method for traditional Chinese poetry. Another significant study by Goyal, Li, and Durrett [15] examined use of effects of GPT-3 on text summarizing with a particular emphasis on the traditional benchmark task of news summarization. Comparative studies indicated how zero-shot GPT-3 stacked up versus refined models developed using sizable summarization datasets. In [20] the researchers created GPT-NeoX-20B, an autoregressive language model with 20 billion parameters which was trained on the Pile and whose weights were made freely and was publicly available to users through a permissive license. The model weights as well as the training and evaluation algorithms are open-sourced. The GPT-NeoX-20B model performed much better when assessed five times with comparable-sized GPT-3 and FairSeq models.

The medical community has been under increasing pressure to keep up with the accelerated proliferation of new Corona virus related publications in light of the COVID-19 pandemic. In order to close the gap between researchers and the continuously expanding body of publications, the COVID-19 Open Research Dataset Challenge has made a corpus of academic articles available. Based on keywords retrieved from the source articles, a model developed by Kieuvongngam, Tan, and Niu [21] gave abstractive and complete information. The model was an effort to generate concise summaries of papers for which there were no existing abstracts, which could provide better assimilation of knowledge for the medical community. The widespread emergence of antibiotic resistance in pathogens as addressed by

Mashalidis and Lee [22] necessitated the creation of antibacterial medicines that can hinder untapped targets in bacterial metabolism. Insights into MraY inhibition that are compatible with known inhibitor activity data have been provided by a number of recent structures of MraY (Phospho-MurNAc-Pentapeptide Translocase) enzyme and its human paralog, GlcNAc-1-P-Transferase using GPT -3 which can guide rational drug design for this crucial antibiotic target.

In the past, cutting-edge NLG architectures like RNN and LSTM had vanishing gradient issues such as sentences grew longer, the distance between places remained linear, and since sentences were processed word by word, sequential processing made parallelization difficult. In 2021, Topal, Bas, and Heerdenx [23] conducted more research on Transformers that have become more prevalent in Natural Language Generation and attention techniques have proliferated (NLG). In [24], the researchers suggested a brand new system named Scarecrow for using crowd sourcing to annotate machine text. The ten error categories of Scarecrow such as redundancy, commonsense errors, and incoherence are mainly determined by numerous rounds of crowd annotation experiments without a preset ontology in order to enable the wide range of real machine errors that can be recognized by lay people. The findings of Meng, Bau, Andonian, and Belinkov [25] support the critical function of mid-layer feed-forward modules in storing factual associations and imply that model modification may be made possible by directly manipulating computational mechanisms. The accompanying materials can include the code, dataset, graphics, and an interactive demo notebook. GPT-3 can be seen just as one example of how very large scale statistical language models have significantly advanced the field recently. Without using any explicit programming or rules, it is competent of internalizing linguistic rules. Instead, GPT-3 learns language by repeated exposure, albeit on a much bigger scale than a human infant would. Without clear standards, it can sometimes struggle with even the most basic linguistic tasks, but more often can also succeed at more challenging ones like copying authors or waxing lyrical.

From the literature review, it is evident that GPT has been able to create major leaps in different applications from word prediction for English and other languages to biomedical sciences. Therefore, we also need to understand the functioning and applications of GPT- 3 model in particular to determine the different facets of futuristic expected behavior and benefits.

IV. DATA COLLECTION

The data has been collected to conduct exploratory research from various secondary sources that include notable research literature published and available from various online sources such as SSRN, arXiv, ScienceDirect, and other sources.

V. DATA ANALYSIS AND DISCUSSION

A. The GPT-3 Model

GPT-3 can write functional code that can be executed without mistake with just a few snippets of example code text, as programming code is nothing more than a type of text. Additionally, GPT-3 has been effectively applied to create website mockups. One developer has merged the UI prototyping software Figma with GPT-3 to enable the creation of web pages with only a little amount of recommended text. Even website clones have been created with GPT-3 by using a URL as recommended text. Developers use GPT-3 in a wide range of methods, including producing code snippets, regular expressions, plots and charts from text descriptions, Excel functions, and other development applications [1].

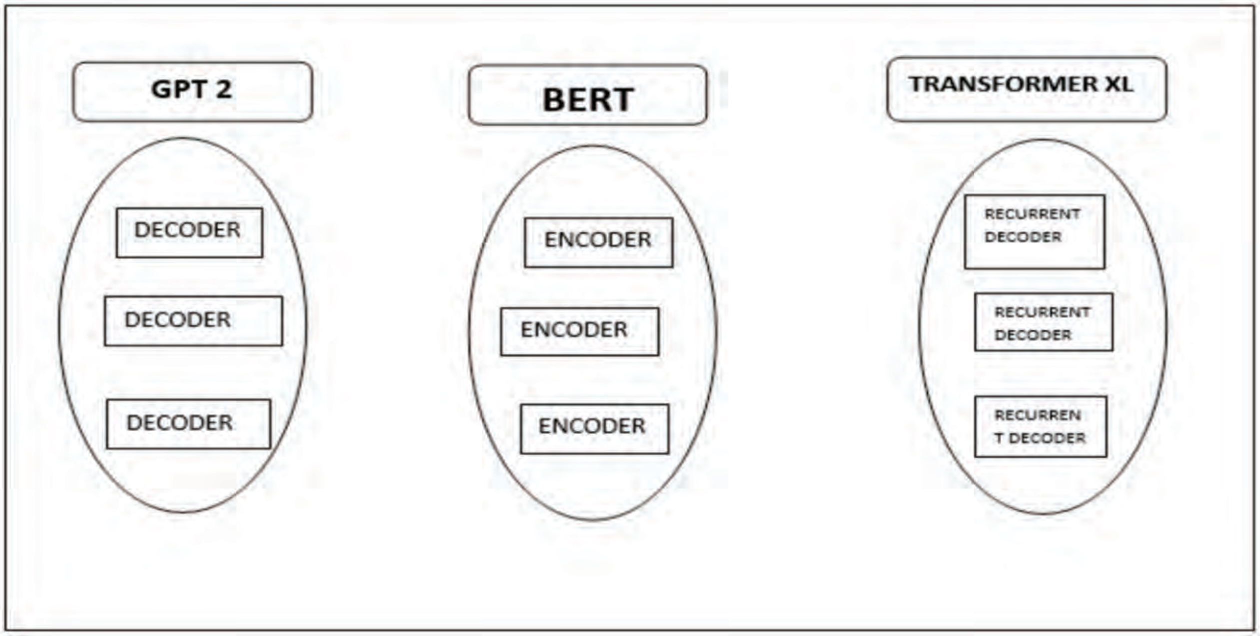
B. GPT3 Process Model

(1) *GPT-3 components*

As seen in Fig. 1, GPT- 3 includes decoders; BERT is inclusive of all the encoders while the Transformer XL includes Recurrent Decoders which continuously updates the output based on recurrent inputs from the environment based on the context [2].

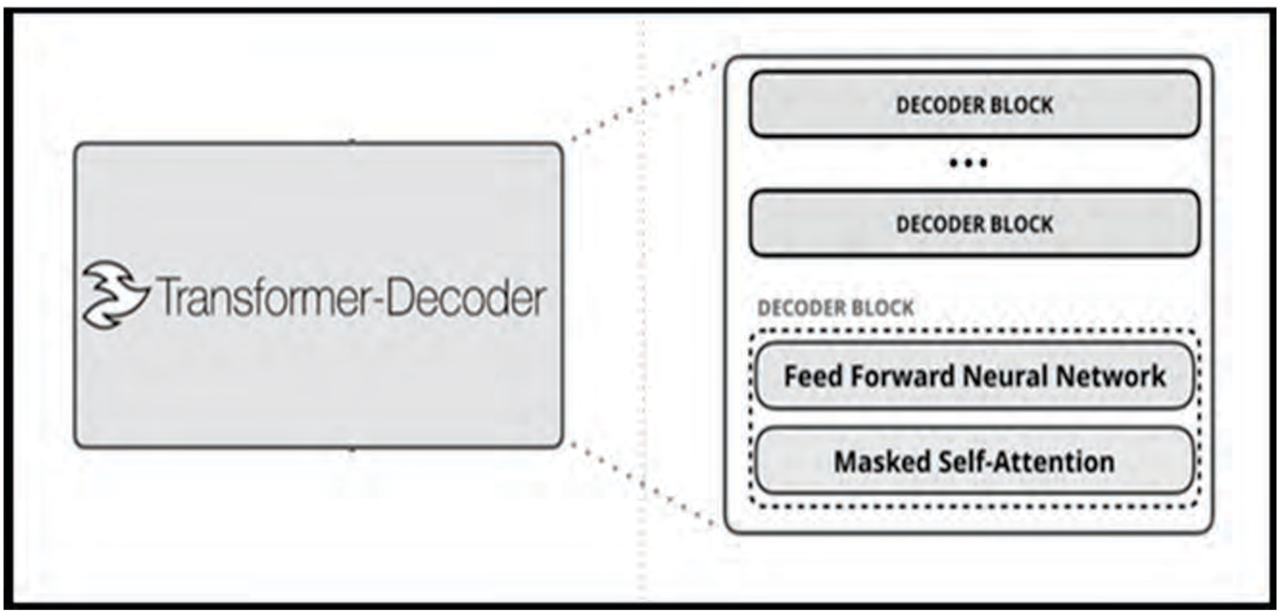
(2) *The Transformer-Decoder*

As seen in Fig. 2, the transformer-Decoder [2] continuously decodes new information based on the predictability of the next possible word (output) based on the context of the meaning and appropriability of the word in view of the context. Each Decoder block functions based on the feed forward neural network model. Further, this function assigns scores to how



(Source : Author)

Fig. 1. The GPT Transformer



(Source: https://jalammar.github.io/illustrated-gpt2/)

Fig. 2. The Process Model of GPT-3

relevant and appropriate each word in the segment is in the form of vector representation.

(3) ***Masked Self-attention***

The Self-Attention Process can be understood through its components (vectors). Each token in the section is

Word	Value vector	Score	Value X score
<s>		0.0001	
walk		0.3	
in		0.4	
a		0.002	
straight		0.003	
line		0.5	
		SUM	

(Source : Author)

Fig. 3. Process of Masked Self Attention

processed for self-attention. Three vectors are significant components:

(i) Query : The query is a representation of the current word that is used to score against all other words (using their keys). We only worry about the token query we are now processing. (i.e. current word under consideration only against other words).

(ii) Key : Key vectors act as labels for all of the words in the segment. They are what we match against when looking for relevant words (key #1,2,3) .

(iii) Value: Value vectors are genuine word representations; after determining how relevant each word is, they are the values that we mix together to form the current word (value # 1,2,3).

We multiply each value by its score and add them together to get our self-attention result. This weighted blend of value vectors results in a vector that paid 50% of its “attention” to the word 'line', 40% to the word 'in', and 30% to the word 'walk'. Merely choosing the token with the greatest score (top k = 1) is sufficient. However, if the model takes into account other words, the outcomes can be improved (CONTEXT). A better technique would be to sample a word from the complete list, with the score indicating the likelihood of selecting that word (so words with a higher score have a higher chance of being selected). The model has now finished an iteration that resulted in the output of a single word. The model iterates until either the complete context (1024 tokens) or an end-of-sequence token is created (Fig. 3) [2].

(4) *Applications of GPT Models*

(i) Algolia

The greatest search and discovery platform for businesses is Algolia, which also enables Builders to create exceptional experiences. This AI model from OpenAI, GPT-3, gives customers easy access to product catalogues [26].

(ii) MessageBird

MessageBird offers an omnichannel communications platform with the integration of a GPT-3 powered tool. It helps to enhance every interaction while optimizing authentications and video meetings for marketing and sales [26].

(iii) Debuild.co

One of the best GPT-3 powered apps is Debuild.co, which can be used to quickly and efficiently construct web applications. With just one click, SQL code can be generated and an interface can be put together visually. It makes use of this AI model to develop an autonomous software writing system at the same calibre as the most experienced developers [26].

(iv) Tabulate

For deriving best financial back-office solution, Tabulate combines industry accounting experts with unique technology using the AI model GPT-3. It provides several services including accounts payable, payroll, analytics, bookkeeping, and tax preparation [26].

(v) CopyAI

CopyAI is a well-known GPT-3 powered tool to automate creativity tools and generate marketing copies within a short period of time efficiently. This AI model may be used by businesses for sales copy, blog posts, e-Commerce copy, website copy, social media content, and digital ads [26].

(vi) AI Channel

AI Channel is one of the top GPT-3 powered apps and a social network platform for allowing collaboration with artificial intelligence agents. It helps companies or individuals to have a conversation with the AI model to understand natural language. The AI Channel app interface is like a messaging application UI including a directory of different conversations [26].

(vii) Snazzy AI

The most straightforward method for using GPT-3 to create content is offered by Snazzy AI. With just three clicks, you may access a variety of services, such as developing landing pages, copywriting, Google Ads, and more [26].

(viii) Writesonic

One of the popular GPT-3 driven apps to improve a website's SEO and increase traffic is Writesonic. This AI model generates high-quality articles, emails, blogs, landing pages, and many more within a short period of time [26].

(ix) Grok

Grok is a popular GPT-3 powered tool that utilizes the advanced AI model known as GPT-3 to summarize the on-demand and daily digest of subscribed channels. It can summarize the last 30 messages in any Slack channel with the Grok Conversation Summary [26].

(x) OthersideAI

OthersideAI offers HyperWrite which is one of the top GPT-3 powered applications as the most powerful document editor to compose beautiful content within a few minutes. It uses the most cutting-edge AI model to efficiently and effectively write articles. This GPT-3 powered tool helps to modify texts as longer, shorter, casual, formal, and many more [26].

VI. INFERENCES AND CONCLUSION

(1) The continuous improvement process of encoding, decoding, and recurrent decoding has clearly shown that the algorithm is becoming more and more accurate with training through large datasets.

(2) The selection of most appropriate "word" as an output has improved as number of experiments in different domains such as Language model prediction, biological sciences, Literature models, management models, and other domains have increased manifold with efficiency in predictions and reduction in errors.

(3) The feed forward Neural Network decoder algorithm is continuously getting better in processing in-context data leading to higher accuracy in training, testing, and validation of results.

(4) Some of the major applications can be seen in the business domain of marketing and sales through Algolia, MessageBird. Accounting, and Financial applications include Tabulate while E-Commerce applications include copyAI.

(5) For website development for apps, Debuild.co is helping in writing better SQL codes, while website landing, copywriting online advertisement designing is being supported by Snazzy AI, and writing better content is aided by Writesonic, otherside AI.

(6) Conversation applications have also been simultaneously developed which include AI channel and Grok.

Therefore, from the study of literature and inferences, we can observe that GPT is here to stay and will continuously improve as it touches and experiences variety of data over multiple domains. It might combine the improvements and learning from various applications and might also merge into a convergence of knowledge benefitting leading to solution for the most complex problems in future. As also evident from recent developments, GPT-4 models are also in the course of development and numerous varied solutions as a result of such convergence might appear in the near future.

VII. FUTURE WORK

The current work is limited to the evolution and some of the applications of GPT-3. In future, more detailed research into the extensive applications of GPT-3 and beyond may be undertaken.

AUTHOR'S CONTRIBUTION

Prof. Sandeep Bhattacharjee conceptualized the research, conducted the interview, and prepared the draft transcript. Prof. Sandeep Bhattacharjee worked on the literature review, collection of industry information, and revised the draft. He finalized this article.

CONFLICT OF INTEREST

Prof. Sandeep Bhattacharjee certifies that he has no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in the manuscript.

FUNDING ACKNOWLEDGEMENT

Prof. Sandeep Bhattacharjee has not received any financial support for the research, authorship, and/or for the publication of the article.

REFERENCES

[1] "OpenAI." Wikipedia.org. https://en.wikipedia.org/wiki/OpenAI#GPT

[2] J. Alammar, "The Illustrated GPT-2 (Visualizing Transformer Language Models)." Jalammar.github.io. https://jalammar.github.io/illustrated-gpt2/

[3] N. Thompson and S. Spanuth, "The decline of computers as a general purpose technology: Why Deep Learning and the end of Moore's Law are fragmenting computing," 2018, doi: 10.2139/ssrn.3287769.

[4] L. Floridi and M. Chiriatti, "GPT-3: Its nature, scope, limits, and consequences," *Minds and Machines*, vol. 30, no. 4, pp. 681–694, 2020.

[5] Z. Yang, Z. Gan, J. Wang, X. Hu, Y. Lu, Z. Liu, and L. Wang, "An empirical study of GPT-3 for few-shot knowledge-based VQA," in *Proc. AAAI Conf. Artif. Intell.*, 2021, doi: 10.48550/arXiv.2109.05014.

[6] N. Dehouche, "Plagiarism in the age of massive Generative Pre-trained Transformers (GPT-3)," *Ethics Sci. Environmental Politics*, vol. 21, pp.17–23, 2021.

[7] W. L. Benzon, "GPT-3: Waterloo or Rubicon? Here be Dragons, Version 4.1," Working Paper, Version 2, 2020. https://ssrn.com/abstract=3667608

[8] J. Liu, D. Shen, Y. Zhang, B. Dolan, L. Carin, and W. Chen, "What makes good in-context examples for GPT-3?," 2022. http://arXiv:2101.06804

[9] J. Klinger, J. C. Mateos-Garcia, and K. Stathoulopoulos, "Deep Learning, Deep Change? Mapping the development of the Artificial Intelligence general purpose technology," 2018, doi: 10.2139/ssrn.3233463.

[10] Y. Yang, Y. Li, and X. Quan, "UBAR: Towards fully end-to-end task-oriented dialog system with GPT-2," in *Proc. AAAI Conf. Artif. Intell.*, vol. 35, no.16, 2021, pp. 14230–14238.

[11] J.-S. Lee and J. Hsiang, "Patent claim generation by fine-tuning OpenAI GPT-2," *World Patent Inform.*, vol. 62, 2020, 101983, doi: 10.1016/j.wpi.2020.101983.

[12] D. Ham, J. G. Lee, Y. Jang, and K.-E. Kim, "End-to-end neural pipeline for goal-oriented dialogue systems

using GPT-2," in *Proc. 58th Annu. Meeting Assoc. Computational Linguistics*, 2020, pp. 583–592, doi: 10.18653/v1/2020.acl-main.54 .

[13] K. Elkins and J. Chun, "Can GPT-3 pass a writer's Turing test?," *J. Cultural Analytics*, vol. 5, no. 2, pp. 1–16, 2020, doi: 10.22148/001c.17212.

[14] T. Klein and M. Nabi, "Learning to answer by learning to ask: Getting the best of GPT-2 and BERT worlds," 2019. [Online]. Available: http://arXiv:1911.02365

[15] T. Goyal, J. J. Li, and G. Durrett, "News summarization and evaluation in the era of GPT-3," 2022. [Online]. Available: http://arXiv:2209.12356

[16] K. McGuffie and A. Newhouse, "The radicalization risks of GPT-3 and advanced neural language models," 2020. [Online]. Available: http://arXiv:2009.06807

[17] M. Mager, R. F. Astudillo, T. Naseem, M. A. Sultan, Y. S. Lee, R. Florian, and S. Roukos, "GPT-too: A language-model-first approach for AMR-to-text generation," 2020. [Online]. Available: http://arXiv:2005.0912 3

[18] W. de Vries and M. Nissim, "As good as new. How to successfully recycle English GPT-2 to make models for other languages," 2020. [Online]. Available: http://arXiv: 2012.05628

[19] Y. Liao, Y. Wang, Q. Liu, and X. Jiang, "GPT-based generation for classical Chinese poetry," 2019. [Online]. Available: http://1907.00151

[20] S. Black, S. Biderman, E. Hallahan, Q. Anthony, L. Gao, L. Golding, H. Horace, C. Leahy, C., K. McDonald, J. Phang, M. Pieter, U. S. Prashanth, S. Purohit, L. Reynolds, J. Tow, B. Wang, and S. Weinbach, "GPT-NeoX-20B: An open-source autoregressive language model," 2022. [Online]. Available: http://arXiv:2204.06745

[21] V. Kieuvongngam, B. Tan, and Y. Niu, "Automatic text summarization of COVID-19 medical research articles using BERT and GPT-2," 2020. [Online]. Available: http://arXiv:2006.01997

[22] E. H. Mashalidis and S-Y. Lee, "Structures of bacterial MraY and human GPT provide insights into rational antibiotic design," *J. Mol. Biol.*, vol. 432, no. 18, pp. 4946–4963, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0022283620302382

[23] M. O. Topal, A. Bas, and I. van Heerdenx, "Exploring transformers in natural language generation: GPT, BERT, and XLNET," 2021. [Online]. Available: http://arXiv:2102.08036

[24] Y. Dou, M. Forbes, R. Koncel-Kedziorski, N. A. Smith, and Y. Choi, "Is GPT-3 text indistinguishable from human text? SCARECROW: A framework for scrutinizing machine text," in *Proc. 60th Annu. Meeting Assoc. Comput. Linguistics* (Volume 1: Long Papers), pp. 7250–7274, Dublin, Ireland. Assoc. Comput. Linguistics, 2022, doi: 10.48550/arXiv.2107.01294.

[25] K. Meng, D. Bau, A. J. Andonian, and Y. Belinkov, "Locating and editing factual associations in GPT," in *Advances Neural Inform. Proces. Syst.*, 2022.

[26] D. Sinha, "Top 10 GPT-3 powered applications to know in 2022," Analyticsinsight.net. https://www.analyticsinsight.net/top-10-gpt-3-powered-applications-to-know-in-2022/

About the Author

Prof. Sandeep Bhattacharjee has been working as Assistant Professor (Grade- II), Marketing Management at Amity University, Kolkata for four years. He was previously working as Assistant Professor of Marketing at Usha Martin Education and Solutions group. He has more than 11 years of experience with over 10 plus years of experience in academics and a year of corporate experience. He takes keen interest in academic development with teamwork as the essence. His research areas include applied data -mining in marketing and other social areas of development with applied analytics. He has conducted training on SPSS and Statistics modules for academics and industries. He is also certified in business intelligence tools and Data analytics.