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GPT for Management: Ramifying the Business Order

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Abstract

Natural Language Processing (NLP) approaches are emerging and expanding rapidly. The Generative Pre-trained Transformer (GPT) technique allows businesses to handle NLP challenges such as text summarization and question answering. This study examines GPT's historical evolution, operational foundation, and applications of GPT. This study also offers real-world examples of the use of GPT to solve various NLP problems. Most importantly, we critically assess this disruptive technique because it is necessary to understand the benefits and limitations of new technology to avoid negative effects. Finally, we discuss the future of GPT as well as the technological and societal ramifications of this new disruptive technology.

Keywords

Natural Language Processing, GPT, Supervised Learning, Unsupervised Learning, Content Creation.

1. Introduction

The field of Natural Language Processing (NLP) has experienced tremendous growth. The Generative Pre-trained Transformer (GPT) can solve NLP issues such as text summarization, reading comprehension, question-answering, and machine translation. In the past, supervised learning models were employed to handle NLP problems, but these models have their own drawbacks, such as the need for labelled data, the inability to generalise to new data, the potential for overfitting, etc. (Radford et al., n.d.). While GPT employs unsupervised learning models, these models outperform supervised learning techniques in the majority of cases and achieve accuracy levels that are nearly identical to them (Kitaev et al., 2020).

GPT is an artificial intelligence model that produces text that resembles that of a person. It operates by a method known as pre-training, the model is trained on a vast dataset of text. This enables the model to develop an understanding of the patterns and structure of language and to produce content that is cohesive and flows organically (Baduge et al., 2022).

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One of the most important characteristics of GPT is its capacity to consider the words that come before and after a certain term, enabling it to produce text that is pertinent and acceptable in a given context (Brown et al., 2020). Language translation, text summarization, and content creation are just a few of the potential uses for GPT. It has been applied to a number of different fields, such as language modelling, chat boots, and question-answering.

Furthermore, by using GPT across several domains, it has the ability to disrupt the commercial sector. As such, it enables the generation of marketing/advertising material, the creation of conversation boots, the study of massive datasets for financial forecasts, the improvement of supply chain efficiency, and sentiment analysis (Baduge et al., 2022). It has the potential to transform a vast number of existing traditional business activities through context analysis at a lower cost. Therefore, it offers the opportunity to help in improving the data analysis and expediting the decision-making processes (Singhal et al., 2021).

While exploiting the potential of new-disruptive technologies, specifically based on deep learning, it is equally vital to comprehend the working framework, potential advantages and limitations associated with them to mitigate risks and avoid the technical and social consequences. Therefore, the purpose of this study is to define the GPT's evolution, functioning mechanism, benefits, limits, and future potential in the context of the business sector. The remainder of this paper is organised as follows: section two presents the historical development and related work of GPT. This is followed by highlighting its working framework, uses, and business applications. After that, in section four, some case studies that demonstrate the adoption of GPT along with its benefits and limits. Section five critically evaluate the GPT which is followed by the future of GPT in businesses. Finally, section seven offers the concluding remarks of the study.

2. GPT: Review and Historical Development

2.1. Historical Development

GPT is an artificial intelligence model that is meant to create text that is similar to that of humans. GPT is essentially a Natural Language Processing tool (NLP). The origins of NLP may be traced back to the 1950s, when the worldwide scientific community grew interested in understanding computers' capacity to exhibit intelligent behaviours and imitate human thought. Due to limited processing power and systems dependent on large sets of handwritten rules and a restricted vocabulary, development remained slow until 1990. With the introduction of machine learning and the continual development in processing capacity, interest in research and applications has gradually increased. Recent key advancements in NLP include speech recognition, language processing, dialogue systems, and the use of deep learning techniques.

One of them is GPT (Generative Pre-trained Transformer) technique which is based on unsupervised models of deep learning and capable in understanding context analysis. GPT technology has evolved through time, with some significant milestones as shown in Table 1.

Table 1

Significant Milestones in GPT Evolution

Platforms	Based on	Description
Word2Vec (2013)	Word embedding	Word2Vec is a NLP technique for creating word embedding. In 2013, Tomas Mikolov and his team at Google created it. Word2vec learns to vectorise words from a vast corpus of texts.
Seq2Seq (2014)	Encoder-decoder architecture	Google developed the "Sequence to Sequence" (Seq2Seq) framework, which could translate text from one language to another. Seq2Seq employed an encoder-decoder structure, with an encoder processing input text and a decoder producing output text.
GPT (2017)	Pre-training	The OpenAI model "GPT" was able to create human-like writing. GPT employed a technique known as pre-training, in which the model was trained on a huge text dataset. Pre-training teaches the model the structure and patterns of language, allowing it to create content that is cohesive and flows organically.
GPT-2 (2018)	Pre-training with large model size	OpenAI published a GPT-2 (Generative Pre-training Transformer 2) model that was significantly larger and more powerful than the previous GPT model. GPT-2 produced high-quality text and performed well on a range of NLP tasks.
GPT-3 (2020)	Pre-training	GPT-3 is the largest and powerful GPT model to date. GPT-3 is capable of performing a wide range of NLP

	with large model size	tasks and has been utilised in a number of applications such as language translation and content generation.

GPT and related approaches have advanced historically from basic word embedding to strong models capable of generating high-quality text and performing a number of NLP tasks. GPT-3 is a language model, it is quantitative algorithm that evaluates potential word embedding (Sagar, 2020). Due to a massive dataset, GPT-3 has witnessed a number of conversations and can predict which word should come next based on the words around it (Kaur et al., 2021). GPT-3 has been extensively structured on billions of cut-off points, and it now simply requires a predefined amount of prompts or advisers to complete the specific assignment you desire, which is known as shot learning.

2.2. Related Work

Several research have focused on expanding the number of parameters in language models in order to improve generative or task performance. Research along these themes has gradually increased model size: 213 million parameters, 300 million parameters (as shown in Figure 1). An early work-built LSTM-based language models to even more than a billion parameters. Several efforts have been undertaken to investigate the influence of scale on language model performance, with the goal of discovering a smooth power-law trend when autoregressive language models are scaled up.

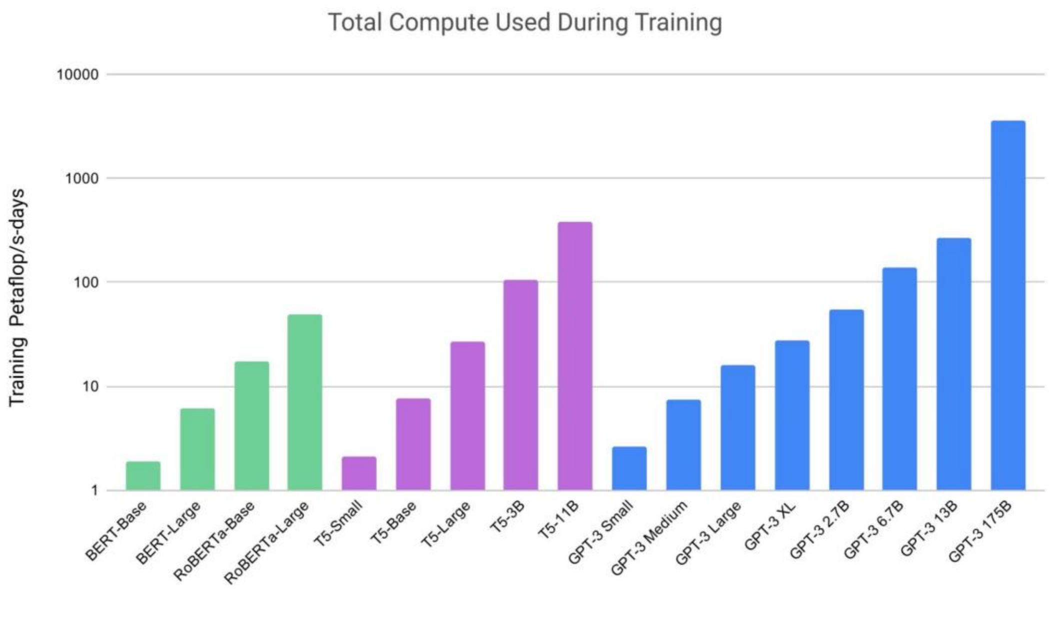

Figure 1: Total Compute Used During Training (Brown, Tom B., et.al.)

This study provides an overview of the discipline of Natural Language Processing (NLP) models. It discusses how OpenAI developed their landmark model GPT-3, which analyses words simultaneously rather than memorising whole sequences as was the case with Recurrent Neural Networks (RNN) (Chen et al., 2018). Other substantial language models, including Microsoft's Turing-NLG and Google's BERT, are also mentioned in the article. As measured by parameters and training dataset sizes, AI progress has been moving toward bigger size for various sorts of models (Bender et al., 2021). GPT-3's ability to perform tasks like summarising texts, answering questions, translating, etc. with few or no user-supplied examples is known as few shot learning and has attracted significant interest from a variety of communities, including the machine learning industry, the media, ethics, civil society, etc.(Tian & Zhu, 2016).

3. GPT: Working Framework & Applications

In order to comprehend the working mechanism of GPT, some concepts must be understood. All of these ideas are related to GPT models in some manner. And how these are connected to one other and GPT-3 will be demonstrated in next sub-section.

1. **Language models**: Jason Brownlee defines language models as "probabilistic models that are able to predict the next word in the sequence given the words that precede it." These models are capable of performing a wide range of NLP tasks, including machine translation, question-answering, text summarization, and image captioning.
2. **Transformers**: This neural network type first developed in 2017 as a unique framework for solving various machine learning tasks. The developers wanted to eliminate recurrent neural networks (RNNs) and convolutional neural networks (CNNs) in order to rely solely on attention mechanisms.
3. **Generative models**: In statistics, there are two types of models: discriminative and generative models, which are frequently employed to accomplish classification task. Discriminative models encode the conditional probability of a given pair of observable and target variables(Tu, 2005). Generative models encodes the joint probability (GM et al., 2020). The crucial point to consider is that generative models can produce new data that is comparable to existing data.

4. **Supervised learning:** The different algorithms provide a function that translates inputs to desired outputs. The classification problem is a common formulation of the supervised learning task: the learner is required to learn the behaviour of a function that maps a vector into one of several classes by looking at several input-output examples of the function (Cunningham et al., n.d.).
5. **Semi-supervised learning**: This training paradigm combines supervised fine-tuning with unsupervised pre-training. The idea is to train the model with a large dataset in an unsupervised way, along with to adapt the model to specific task, by using supervised fine-tuning with smaller datasets. This idea solves two problems, first is that it doesn't need expensive labelled data and second is tackled the tasks without large datasets (Radford et al., 2020).
6. **Unsupervised learning:** Unsupervised learning is a sort of machine learning in which models are trained on unlabelled datasets and then allowed to operate on them without supervision. Unlike supervised learning, we have input data but no corresponding output data, unsupervised learning cannot be applied directly to a regression or classification task (Barlow, 1989).

3.1. Working Framework

OpenAI revealed the first edition of GPT for creating texts that seem to have been produced by humans in 2018. The decoder of the transformer serves as the foundation for the GPT design (Vaswani et al., 2017). GPT was trained in two steps. First is, unsupervised pre-training trains GPT on unlabelled text, allowing it to access large amounts of text corpora. And other is, supervised fine-tuning refines the pre-trained model for each labelled task. And finally, input transformation to extract required output from the model.

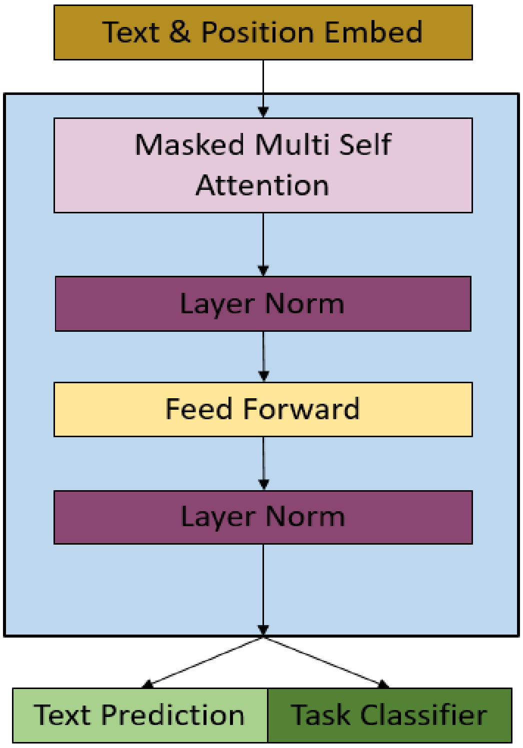

Figure 2: Unsupervised Pre-training (Transformer Architecture) (Radford et al., 2020)

3.2. Uses of GPT

GPT-3 offers a different potential for actual applications. Designers and organisations are only getting started with the possible applications, and it is fascinating what they have learned. The following are a few examples of what GPT-3 means in terms of business.

1) **Application of Semantic Search**: GPT-3 can assist in determining a response to an inquiry or a more vital rundown of events. Rather than only watchword coordination, GPT-3 wide information may be used to quickly and decisively fulfil complicated standard language inquiries.
2) **Content Generation**: GPT-3 can help with anything, including trial composing, instructional content, experience-based games, stuff pages, and portions for the next punk melody. It works well for creating unique items after some basic setup.
3) **Productivity Boosters**: GPT can be used to boost productivity in business by automating repetitive or time-consuming tasks.
4) **Language Translation**: GPT can be used to improve the efficiency and accuracy of language translation for businesses that operate in multiple languages.

5) **Generation of Deep learning models**: It can be used generate deep learning models just by getting the information of the dataset.

GPT-3 has been making news since last summer because to its ability to handle a wide range of natural language tasks and create human-like prose. GPT-3's capabilities include, but are not limited to:

a) Text categorization (i.e. sentiment analysis)
b) Questions answering
c) Text creation
d) Summarization of text
e) Recognizing entities names
f) Translation of a language

3.3. Applications in Business

1. **Product Design:** Artificial Intelligences (AIs) with generative capabilities can create brand-new designs for goods like cars or apparel. This enables businesses to rapidly and effectively explore a variety of design possibilities without having to create each one from scratch (Kerrigan, 2022).
2. **Marketing:** Companies may leverage the marketing and advertising materials that generative AIs can produce, like as social media posts, email campaigns, and video advertisements, to better target their customers and boost the effectiveness of their marketing initiatives (Thiergart et al., 2021).
3. **Content Creation:** GPT systems may be used to produce textual material such as news stories, blog entries, and product descriptions. This capability can save firms time and resources that would otherwise be used on manual content creation (Thiergart et al., 2021).
4. **Fraud Detection:** GPT systems can detect fraudulent activities such as credit card or insurance claim fraud. Generative AIs can detect suspicious behaviour and highlight it for further investigation by examining patterns in massive amounts of data (Gambini et al., 2022).
5. **Recommender Systems:** GPT systems can provide customized suggestions for clients, such as proposing items or services based on previous browsing and purchasing history, assisting businesses in increasing customer engagement and revenue. Natural Language

Processing (NLP) techniques help the businesses in news summarization and developing recommendation system (Goyal et al., 2022).

6. **Optimization:** Generative models may be used to improve a wide range of business operations, including finance, supply chain management and logistics. Generative AIs may assist firms in making more effective use of resources and improving overall performance by analysing data and recognising trends (Dowling & Lucey, 2023).
7. **Predictive Maintenance:** GPT may be used in predictive maintenance by evaluating sensor data from industrial equipment to forecast when maintenance is required and arrange for it in advance. This forewarning can help organizations save money by avoiding unforeseen expenses and extending the life of its requirements (Rosenfield et al., 2020).
8. **Image and Video Generation:** Generative analytics can be used to create realistic images and videos, such as those used in video games, digital avatars, and virtual experiences (Hong et al., 2022; Kaur et al., 2021).

4. Case Studies

GPT-3 has been used in over 300 applications across categories and industries, ranging from productivity and education to creativity and gaming. These applications make use of a variety of GPT-3's features. Some examples are as follows:

1) **Viable**: Viable assists businesses in better understanding their customers by utilising GPT-3 to deliver meaningful insights from customer feedback in simple summaries. Viable uses GPT-3 to identify themes, emotions, and sentiment from surveys, assistance, and other sources. It then extracts insights from the pooled input and generates a summary in seconds.
2) **Jasper**: Jasper is perhaps the most well-known content production tool that assists users in producing vast quantities of material, once users have input a few crucial data regarding their writing work. The GPT-3 technology used by Jasper even includes recently introduced AI image features.
3) **OpenAI**: One of the most well-known online AI authoring tools, CopyAI uses GPT-3 technology to produce material that is ubiquitous and human-like. In fact, it attracts over 4.3 million visitors every month, proving how well-liked it is.
4) **ShortlyAI**: Another excellent AI writing tool for authors and freelancers to assist them overcome writer's block is ShortlyAI. On the GPT-3 language model, it is based. It can

be used to create huge amounts of material fairly, rapidly, and easily, much like the other AI technologies.

5) **Replika**: Eugenia Kuyda founded Replika with the intention of developing a personal AI that would assist you in expressing and observing yourself through a useful discussion. It is a place where you may openly express your ideas, sentiments, convictions, experiences, memories, and dreams. It has been created as your- “Private Perceptual World”.
6) **Lyerbird**: Creative expression made possible by artificial intelligence. Within Descript, Lyerbird conducts AI research and is developing a new generation of media editing and synthesis tools that improve the usability and expressiveness of content production.

5. Critical Evaluation

From a business viewpoint, it's critical to comprehend GPT-3's possible uses in particular industries as well as its limitations. There have already been several possible business applications for GPT-3 identified. It is important to remember that GPT-3 should be used to assist and improve business processes rather than as a substitute for human judgement and decision-making. Businesses shouldn't be hesitant to use GPT-3 into their processes because it may be a useful tool for sustaining and growing their operations. The creation of reports and summaries, the development of marketing materials, and customer assistance are some potential applications for GPT-3 in a business (Svetlana et al., 2022). Therefore, it is crucial to comprehend what potential drawbacks a company without a plan for implementing GPT-3 can have.

GPT-3 is a powerful language processing technology, but if a company doesn't have a plan for implementing it, they risk missing out on its potential advantages. Without a strategy for employing GPT-3, a company might not be able to benefit from these disadvantages relative to rivals that are adopting already. However, employing GPT-3 in a professional environment has certain potential risks and difficulties. It could produce secret or private information that jeopardizes business security. The potential for GPT-3 to produce inaccurate or misleading data that may affect a company's reputation or its customers. It is essential to carefully weigh the possible advantages and disadvantages of utilising GPT-3 in operations and to make sure that it is used morally and responsibly. The possibility for GPT-3 to be utilized in place of people, which might have a severe impact on employees and the company as a whole.

Every technology has benefits and drawbacks, and this one is no exception. The difficulties OpenAI has with GPT-3 include malicious technology usage, computing costs, and safety. Once the model is open-sourced, it is easy to exploit it to spread false information, which is harder to stop. This was a key worry with the predecessors as well. It is difficult for anybody other than larger organisations to profit from the underlying technology since the model is so huge and expensive to run. The OpenAI researchers' study included a confirmation of the models' bias, and as a result, they are addressing the problems with use recommendations and possible safety. In contrast to humans who need relaxation, sleep, and time to eat, a trolling or spamming bot may continue for hours on end, raising ethical concerns about the use of bots.

While AI robots like GPT-3 need a lot of data to train and forecast, humans can learn with less information and less complicated procedures. Although AI can execute tasks better than humans in some cases, this does not imply that AI is superior to humans. A poll was done to determine if the journal was written by a human or a GPT after it was seen that the GPT-3 performed well in particular activities like writing them. The end result was that it was unrecognisable and wrote diaries just as well as a person would. Humans usually do better than AI when it comes to human traits like empathy, socialising, and handling complicated jobs with inventiveness. Based on the data, GPT-3 may write biased papers or journals that may be damaging to any institution utilising it without scrutiny since they may be prejudiced against a specific race or culture. It lacks the capacity for rational thought that humans do.

Businesses should determine the precise activities and operations where GPT-3 may help and improve their business in order to incorporate GPT-3 into their current processes and systems. Create a strategy for incorporating GPT-3 into their current processes and systems, which should include instructing their staff on its efficient usage. Think about the possibilities for integrating GPT-3 with existing tools and technology in the organization. Monitor, assess, and, when necessary, make adjustments to the use of GPT-3 in their business activities. Keep up on the most recent GPT-3 innovations and discoveries, and think about how they can affect your business.

6. Future of GPT

GPT-3 allows for the automation of anything using a certain language structure. Businesses may use this technology in a variety of ways, such as by responding to customer enquiries, creating content, condensing a lengthy text, translating languages, and writing programmes. The language model for OpenAI was updated with the release of InstructGPT in January 2022.

Compared to the previous version, GPT-3, it is intended to give more accurate findings and less vulgar language. Researchers employed reinforcement learning from human feedback (RLHF) to develop InstructGPT after starting with a GTP-3 model that had already been trained(Raffel et al., 2020). This implies that scientists provided it instructions on how to behave depending on what humans informed them about their desired results for the AI system, such as making less errors or made-up facts until expressly told differently. The performance of three distinct language models (1.3B, 6B, and 175B) against GPT-3 was compared in a research investigation. The findings demonstrated that the models (InstructGPT) taught with human input performed better at interpreting instructions than GPT-3. In particular, GPT-3 was favoured over the 175B InstructGPT model in 70% of the instances (Floridi & Chiriatti, 2020). Even though it was 100 times smaller than the 175B GPT-3 model, the 1.3B InstructGPT model was picked. This shows that improving a language model does not always require it to be larger. Instead, increasing the quantity of training sessions using human feedback can be a successful strategy for enhancing the performance of the model (Chen et al., 2018).

To address the issues of bias and abuse in GPT-3, OpenAI created the new language model InstructGPT. It does not, however, offer a convincing answer to these problems. InstructGPT creates 25% less hazardous text than GPT-3 when instructed to be polite. However, the outcomes will be far more harmful than GPT-3 if it is encouraged to develop poisonous words. This makes the risk of abuse by bad actors much more serious because OpenAI has prioritised user alignment over moral principles. Additionally, OpenAI admits that InstructGPT does not exhibit bias improvements over GPT-3. Because both GPT-3 and InstructGPT are available, prejudice and manipulation remain important moral concerns.

7. Conclusion

Bias has been extensively supported by a technologically deterministic stance within the NLP business, which has contributed to fears, worries, and justifications concerning GPT-3 and its purposeful exploitation for manipulative goals or unintended harm caused by bias. As a result, analysis of GPT-3 has tended to be speculative or has an unwarranted faith in commercial industry's self-regulatory processes. We have presented the historical evolution of generative NLP approaches and the GPT-3 framework in this study. The technological and social effects of emerging disruptive technologies on business are also a significant contextual aspect for GPT-3. Thus, many answers to the consequences of huge language models will become apparent once wider contexts of socio-technical reliance are highlighted.

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