

Understanding ChatGPT: Impact Analysis and Path Forward for Teaching Computer Science and Engineering

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Abstract

ChatGPT has become the most popular regenerative AI application, used for obtaining responses for queries in different domains. Some responses of ChatGPT reported in the internet are accurate, others are funny, and some are fictitious. This article focuses on the application of ChatGPT for academic instructional purposes in the field of Computer engineering and related majors. The capability of ChatGPT for instructional purposes is evaluated by providing responses to different questions pertaining to these engineering streams. This article explores different opportunities with use cases, ChatGPT can provide in augmenting the learning experience. It also provides scenarios of limitations and modifying the evaluation process to prevent the use of ChatGPT for unethical means of learning.

UNDERSTANDING CHATGPT: IMPACT ANALYSIS AND PATH FORWARD FOR TEACHING COMPUTER SCIENCE AND ENGINEERING *

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ChatGPT has become the most popular regenerative AI application, used for obtaining responses for queries in different domains. Some responses of ChatGPT reported in the internet are accurate, others are funny, and some are fictitious. This article focuses on the application of ChatGPT for academic instructional purposes in the field of Computer engineering and related majors. The capability of ChatGPT for instructional purposes is evaluated by providing responses to different questions pertaining to these engineering streams. This article explores different opportunities with use cases, ChatGPT can provide in augmenting the learning experience. It also provides scenarios of limitations and modifying the evaluation process to prevent the use of ChatGPT for unethical means of learning.

Keywords ChatGPT · Education · Computer Science · Engineering

1 Introduction

The release of ChatGPT [1] at the end of 2022 by OpenAI, an AI company in San Francisco, California is creating both enthusiasm and apprehension in the world, especially among the education community. Renowned philanthropist Bill Gates quoted “Chat GPT is as significant as the internet.”[2] ChatGPT autonomously passed Minnesota University Law School Exam with a grade of C+, the MBA exam of Wharton School with a grade of B-, and the gold standard US medical exam USMLE [3] with an overall score of 60% and demonstrated “a high level of concordance and insight in its explanations.” Another AI program [4], which is heavily trained on medical question-answering databases called the MultiMedQA achieved 67.6% accuracy in USMLE. Several other reports of ChatGPT generating meeting agendas of a corporate all hands, assisting programmers in writing C++ and Python code, generating sonnets, and both writing and evaluating high school essays have created fascination among the public. People in several domains of white-collar jobs are feeling their careers become abruptly irrelevant because of the efficiency and accuracy demonstrated by the ChatGPT in their professional deliverables. A standard reply for querying ChatGPT about what it is? provides the following responses.

Prompt: Who are You?

"I am ChatGPT, a large language model created by OpenAI. I am designed to respond to questions and engage in conversation on a wide range of topics. My purpose is to assist and provide information to those who interact with me."

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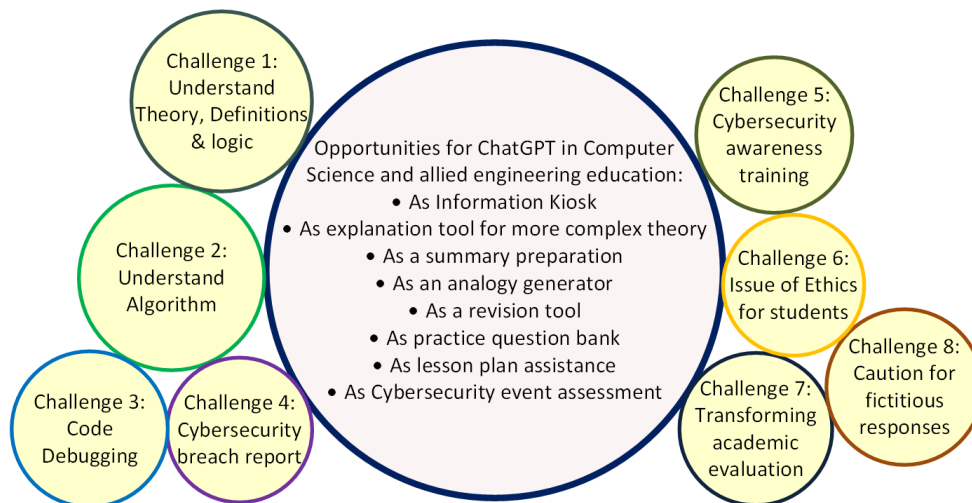


Figure 1: Summary of ChatGPT in Computer Science and allied engineering education

Prompt: Can you elaborate?

-

"Sure! I am an artificial intelligence language model designed to process and understand natural language input, and generate human-like responses. My training is based on a large dataset of text, which allows me to understand various topics and generate responses that are relevant and informative.

When users interact with me, they can ask questions, request information, or engage in conversation on a wide range of topics. I use advanced natural language processing algorithms to analyze and understand the input, and then generate a response that is appropriate and relevant to the query.

My purpose is to assist users in obtaining information, clarifying their understanding of various topics, and engaging in productive conversation. I am constantly learning and improving my abilities through ongoing updates and refinement of my training data."

ChatGPT or Generative Pretrained Transformer with a Chat interface does not claim to be an all-knowing, super intelligent, critical thinking machine, but it is a large language model (LLM), a machine-learning system that autonomously learns from the massive data set of text to generate human-like text. GPT-3 has the ability to perform a wide range of language tasks, including translation, summarizing, question answering, and text generation. It can be fine-tuned on specific tasks or used to generate text in a more general sense.

Google also step up the AI chat war by announcing BARD [5], which is presently on a waitlist (during manuscript preparation). The other alternative is the announcement of ChatGPT with GPT-4 which is in the training phase and expected to release shortly. Hence, the focus of this paper is ChatGPT with GPT-3, which is available and stable.

This paper explores the application of ChatGPT in the domains of Computer Science and Engineering, Electrical Engineering, and Robotics with some sample queries and analyzes the quality of the responses provided by ChatGPT. The paper touches on means of identifying assignments and narratives that are assisted by ChatGPT, the development of plagiarism tools compliant with regenerative AI, and the moral question of using ChatGPT by students. The paper also highlights the issue of transforming academic assessment in a world dominated by regenerative AI. This is summarized in Fig 1.

1.1 Metrics for Evaluation of Intelligence of AI system

The early work of Binet and Simon [6] on distinguishing quick learners and slow learners was based on a wide variety of questions that included the ability to name objects, define words, draw pictures, complete sentences, compare items, and construct sentences. A general intelligence factor was proposed by Charles Spearman and colleagues [7] for quantifying abstract thinking and that includes the abilities to acquire knowledge, to reason abstractly, to adapt to novel situations, and to benefit from instruction and experience.

Intelligent Quotient (IQ) test [8] is a modern method, which is a total score derived from a set of standardized tests or subtests designed to assess human intelligence. The most commonly used individual IQ test series is the Wechsler Adult Intelligence Scale (WAIS) for adults and the Wechsler Intelligence Scale for Children (WISC) for school-age test-takers. Other commonly used individual IQ tests (some of which do not label their standard scores as "IQ" scores) include the current versions of the Stanford–Binet Intelligence Scales, Woodcock–Johnson Tests of Cognitive Abilities, the Kaufman Assessment Battery for Children, the Cognitive Assessment System, and the Differential Ability Scales.

In general, measuring intelligence is a challenging problem because of the multi-faceted nature of the concept of intelligence. For an artificial intelligence (AI) system, rather than general intelligence, the performance is measured with respect to a specific task, or domain problem. The task often depends on the application area, or the nature of the data involved, for instance:

1. Text: automatic translation, document classification, structuring and summary, recognition of named entities, answering questions, etc.
2. The log file: cybersecurity.
3. Speech: automatic speech recognition, language and speaker identification, spoken word detection, translation, etc.
4. Video and image: object recognition, head detection, person tracking, optical character recognition, person recognition, identification.
5. Sensor measurements used in robotics or for autonomous vehicles.

Various metrics have been used to evaluate different tasks performed by an AI system depending on the task at hand, e.g., for clustering (within-cluster and between cluster distances), classification (precision, recall, F1-score, AUC-ROC (area under the receiver operating characteristics curve, Matthew’s correlation coefficient(MCC)), regression tasks (mean square error, mean absolute error). However, these metrics do not necessarily measure the analytical capability of an AI system vis-a-vis human capability. Applying IQ metrics to AI may not be accurate as major AI systems are designed for a specific task as compared to the multi-functional activity of humans. In contrast, ChatGPT intends to replicate the sublime intelligence of human capability which makes the AI evaluation metric insufficient. On the other hand, the IQ metric is still not suitable for the performance evaluation of ChatGPT as those metrics are based on definitive question-and-answer patterns. It does not include abstract capability and uncertainty in the responses. Hence, there is a requirement of designing a regenerative AI-relevant metric that should address the following points:

1. Correctness: The response of a regenerative AI system should stick to facts provided that the opinion sought is related to established topics on science, history, geography, administration, finance, etc. The scope of generating fictitious references and synthetic responses should be limited to the topics of summary generation, creative writing, storytelling, humor, and entertainment.
2. Relevance: The response of the regenerative AI system should accurately correlate with the questions asked to such system. Specifying irrelevant facts and information should add a penalty to the performance metric for evaluating regenerative AIs.
3. Repeatability: It is well known that the response of a regenerative AI system substantially varies when the question is asked several times. This creates a challenge for crediting regenerative AI with a fixed response template. The intelligence metric must take into account the nature of the varying response of regenerative AIs, but also keep in mind the basic facts that the response should cover.
4. Completeness: The metric must also reward responses that cover all the known facts for a factual question.
5. Randomness: The scope of randomness makes each and every response of ChatGPT unique. The required intelligence metric should credit positively for this feature.
6. Fiction: The required intelligence metric should penalize for generating fictitious references for facts-based questions. There should be no room for synthesis when asked to provide references. The response may only contain some fictitious texts for non-fact-based questions.
7. Creativity: The required intelligence metric should reward fictitious creativity when asked to answer non-fact-based questions.

1.2 Knowing vs Thinking

The purpose of education is for students to know and think. ChatGPT demonstrates, how knowing and thinking are not the same thing. Knowing is committing facts to memory; thinking is applying reason to those facts. The chatbot knows everything on the internet but is incapable of critical thinking.

The plethora of impeccable essays on a wide variety of topics generated by ChatGPT may often trick us to assume that ChatGPT is a "deep" thinking machine. This view is reinforced as there are several instances when ChatGPT accepts the incorrect response and then reformulates the response to conform to the hint provided by the user. However, the underlying technology of ChatGPT is a sophisticated language synthesis program. Given this fact, when ChatGPT is confronted by questions with deep underlying thinking requirements, it generates flawed results, makes things up, and irrelevant justification, but with impeccable English. ChatGPT is only capable of relating questions to a specific context and responds with facts or creativity depending on the questions.

An instance of testing ChatGPT for detecting network vulnerabilities [9] leads to the identification of some credible security threats and malware development. Such a response requires some amount of inference and deduction, but its credibility goes for a toss when it also provides an equal number of synthetic threats that were actually unfounded.

Observations such as the above have led to a vigorous debate on whether AI tools such as ChatGPT can indeed lead to any significant improvement in the teaching, learning, and evaluating objectives [10, 11] that were long overdue in our curriculum.

The advent of ChatGPT and other similar LLM tools might accelerate the steps toward developing students that are better thinkers, rather than just simple information repositories.

2 Related Work on ChatGPT and Education

The two articles in The Atlantic about the death of the college essay [12] and the end of high school English [13] has created shockwaves in the educational community. In [12], Marche elaborates on the importance of humanities in an AI LLM world as well as the requirement of understanding AI LLM for humanists. Herman [13] on the other hand is astounded by the quality of the essay ChatGPT produces for different topics. Writing a good essay still requires lots of human thought and work. Indeed, writing is thinking, and authentically good writing is authentically good thinking. However, Steve Nouri in a [14] suggested that users should take a step back and thoroughly investigate the capabilities of ChatGPT so as to determine the appropriate level of confidence in using use ChatGPT.

Nouri advises the user of ChatGPT to obtain sufficient expertise of its capability before it can be completely trusted with its response. A poll also conducted by Nouri [15] on the use of chatGPT in education shows that 21% of voters believe ChatGPT should be banned, 34% believe it should be allowed with strict guidelines, 21% believe it should be allowed with minimal guidelines, and 24% believe it should be allowed with no guidelines.

In a report from The Brookings Institution [16], Kathy and Elias argued that it is a valuable tool to promote, not limit—critical thinking by using the initial response of the bot and then improving on it. They pointed out that ChatGPT is only a threat if our education system continues to “*pursue rubric points and not knowledge*” but could be turned into a friend if we strive for more deeper and engaged learning. In [17], Harris listed the following ways in which the bot can be seamlessly integrated into school education:

1. Google or Wikipedia alternative: get information regarding any topic, ask additional questions to clarify facts.
2. Definitions and explanations: Get definitions on different topics and also seek explanations with different complexity levels. For example, “*Explain the period of Reconstruction in the U.S. suitable for a 5th grader.*”
3. Generate summaries: ChatGPT can generate summaries of concepts, historical events, and pieces of text.
4. Examples: Generate examples of text related to any topic as a starting point before the students elaborate on it.

5. Edit and improve writing: Use the chatbot for quick feedback! Students can paste a piece of writing into ChatGPT and request edits and revisions, including fixing grammatical errors, adding transitional phrases, higher-level vocabulary, and even quotes or facts to back up claims.
6. Formulate questions: Get sets of questions as an assignment for evaluation.
7. Create lesson plans: generating lesson plan with specified objectives and level of complexity for curriculum development.

In a related work, Peter Greene [18] advocated that formulaic, mediocre writing performance will end for good and only original and good pieces of work may be refined using the bot response. In [19], Cherie Shields, a high school English teacher in Oregon, Portland, USA assigned students to use ChatGPT to create outlines for their essays and then elaborate on them. Google CEO Sundar Pichai stated “*AI has the potential to transform education, personalizing learning and enabling students to learn at their own pace.*” [20] He stressed that English and Math are the subjects that will have maximum impact. Vocabulary refining, fresh ideas for writing lessons, storytelling, comprehension, and translation are examples where ChatGPT can be used effectively for English subjects. Math subjects can use it for generating practice problems, step-by-step explanations, and quizzes, and as a personalized instructor for slow-paced learners.

Innovative methods for teaching Computer Science and Power Engineering in more interactive ways are suggested in [21]. Cyber heavy Smart Grid course for modern power system operation and control is proposed in [22]. The specified course covers Communication, Data Management, and Cyber Security along with basic power systems. All hands on deck brainstorming on the methods and scope of teaching modern computer engineering courses by prominent academicians is presented in [23]. Data Science Education specific challenges and issues are pointed out by Bonnell et.al in [24]. An affirmative argument for interdisciplinary education is provided in [25] for the purpose of designing Autonomous Machines. The strong reason for interdisciplinary education is that the future systems will be a combination of Cyber, Physical, and Social Systems [26, 27, 28].

3 What is ChatGPT

The justification of safeguarding various pitfalls of using AI as compared to its explainability is presented in [29], which also enlisted a few examples of controls that may prove effective in minimizing the risk of AI systems that depend on post-hoc explanation. A brief description of ChatGPT and the application of Decentralized autonomous organizations (DAO) for addressing the problems of human feedback is presented in [30]. The core of ChatGPT is the science of Natural Language Processing (NLP). Typically Language processing tool uses Recurrent Neural Network (RNN) [31] [32], Long -short-term memory (LSTM) [33] and Gated Recurrent Unit (GRU) [34]. Natural language processing uses a sequence of words to extract the meaning of a sentence. Application of RNN in NLP is presented in [35]. The Hidden layers in RNN help to remember the sequence of words (data) and use the sequence pattern for the prediction. However, traditional RNN suffers from the following drawbacks:

1. Exploding and vanishing gradient problems during backpropagation.
2. When applied on a paragraph, RNN may leave out necessary information due to gradient problems and not be able to carry information from the initial time step to later time steps.

The reason for exploding gradient is that RNN also capture irrelevant information in the model.

The LSTM and GRU use gates as an internal mechanism to keep the relevant information in the model. This solves the exploding and vanishing gradient problem. Every LSTM network contains three gates to control the flow of information and cells to hold information.

The "forget" gate decides what information should be carried forward or what information should be ignored. The input gate adds the new relevant information to the existing information by updating cell states. The output gate generates the next hidden states and cell states are carried over to the next time step. To solve the vanishing gradient problem of a standard RNN, the GRU uses update gate and reset gate. The update gate helps the model to determine how much of the past information (from previous time steps) needs to be passed along to the future. The reset gate is used to decide how much of the past information to forget. However, RNNs, including LSTM and GRU all suffer from slow training, and are unable to handle long sequences.

Attention mechanisms [36] is one of the solutions to overcome the problem of model forgetting. This is because they allow dependency modeling without considering their distance in the input or output sequences.

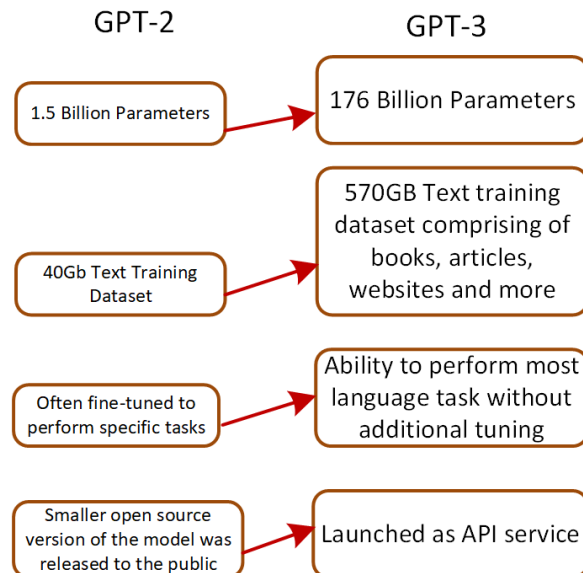


Figure 2: Comparison of GPT-2 and GPT-3

Due to this feature, they have become an integral part of modern techniques for sequence modeling and transduction. The idea behind attention is to:

1. Create three vectors from each of the encoder’s input values (query, key, value)
2. Calculate a score for how much to focus on each part of the input when we encode words at specific positions
3. Select a value (referenced by a key) relevant to a query (what we are trying to pull from input)

Attention mechanism along with transformer is proposed in [37]. The transformer provides an architecture designed to process a connected set of units such as the tokens in a sequence or the pixels in an image—where the primary interaction between units is through self-attention.

3.1 Understanding ChatGPT

Generative Pre-training Transformer (GPT) models were first launched in 2018 by openAI as GPT-1. The models continued to evolve over 2019 with GPT-2, 2020 with GPT-3, and most recently in 2022 with InstructGPT and ChatGPT. Prior to integrating human feedback into the system, the greatest advancement in the GPT model evolution was driven by achievements in computational efficiency, which enabled GPT-3 to be trained on significantly more data than GPT-2, giving it a more diverse knowledge base and the capability to perform a wider range of tasks. Comparison of GPT-2 and GPT-3 is shown in Fig 2

All GPT models leverage the transformer architecture, which means they have an encoder to process the input sequence and a decoder to generate the output sequence. Both the encoder and decoder have a multi-head self-attention mechanism that allows the model to differentially weight parts of the sequence to infer meaning and context. In addition, the encoder leverages masked-language-modeling to understand the relationship between words and produce more comprehensible responses.

A way to account for the order of the words in the input sequence is performed by positional encodings as shown in Fig 3. The transformer adds a vector to each input embedding. These vectors follow a specific pattern that the model learns, which helps it determine the position of each word, or the distance between different words in the sequence.

The encoder starts by processing the input sequence. The output of the top encoder is then transformed into a set of attention vectors. These are to be used by each decoder in its “encoder-decoder attention” layer which helps the decoder focus on appropriate places in the input sequence.

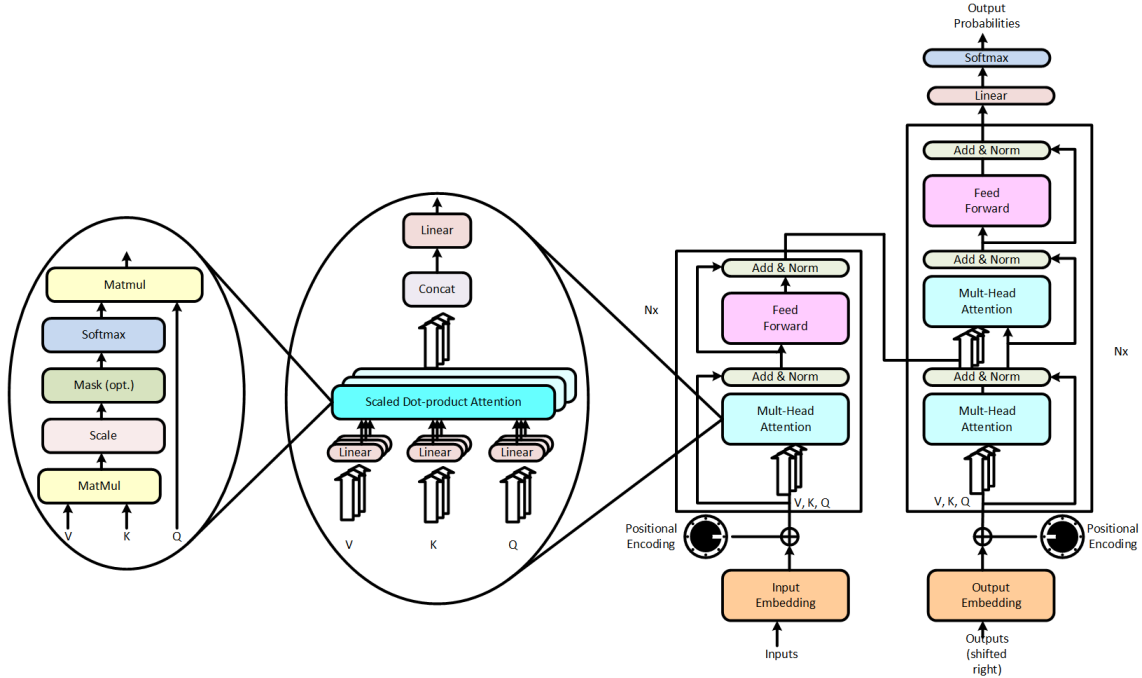


Figure 3: Transformer Architecture

The next step in calculating self-attention is to create three vectors from each of the encoder’s input vectors (in this case, the embedding of each word). So for each word, we create a Query vector Q , a Key vector K , and a Value vector V .

The self-attention mechanism that drives GPT works by converting tokens (segments or pieces of text, which can be a word, sentence, or other groupings of text) into vectors that represent the importance of the token in the input sequence. To do this, the model,

1. Creates a query, key, and value vector for each token in the input sequence by using the following matrix multiplication $Q = X * W_Q$, $K = X * W_K$ and $V = X * W_V$, where W_Q , W_K and W_V are unknown weights matrix to be trained.
2. Calculates the similarity between the query vector from step one and the key vector of every other token by taking the dot product of the two vectors.
3. Generates normalized weights by feeding the output of step 2 into a softmax function. The softmax score determines how much each word will be expressed at this position.
4. Generates a final vector, representing the importance of the token within the sequence by multiplying the weights generated in step 3 by the value vectors of each token.

The paper further refined the self-attention layer by adding a mechanism called “multi-headed” attention which improves the capability of the model of grasping sub-meanings and more complex relationships within the input data in two ways:

1. It expands the model’s ability to focus on different positions. For example, in translating a sentence like “The animal didn’t cross the street because it was too tired”, it would be useful to know which word “it” refers to.
2. It gives the attention layer multiple “representation subspaces”. The multi-headed attention uses multiple sets of Query/Key/Value weight matrices, typically eight sets are used for training, which are randomly initialized.

ChatGPT is further improved by using Reinforcement Learning from Human Feedback (RLHF) [38] as a three-step process of Supervised Fine Tuning, Reward Model, and Reinforcement Learning Model.

Collect demonstration data, and train a supervised policy.

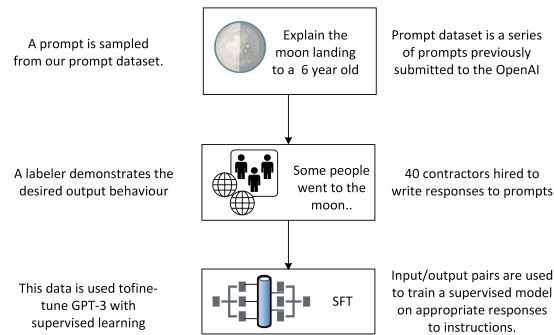


Figure 4: Supervised Fine Tuning

3.1.1 Supervised Fine Tuning (SFT) Model

The first step for fine-tuning the GPT-3 model is performed by generating a supervised training dataset by 40 human experts. The experts prepared standard responses for known inputs on which the model is to be trained as demonstrated in Fig 4[38].

Questions, or prompts, were collected from human users into the OpenAI API. The human experts then wrote an appropriate response to the prompt to create a known output for each input. The GPT-3 model was then fine-tuned using this new, supervised dataset, to create GPT-3.5, also called the SFT model.

A maximum of 200 prompts were accepted from a single user to preserve the diversity of the prompt dataset. The prompts containing long prefixes and personally identifiable information were filtered out.

The experts were instructed to create sample questions to fill up prompt categories having minimal real data samples .

Such categories are:

1. Plain prompts: any arbitrary ask.
2. Few-shot prompts: instructions that contain multiple query/response pairs.
3. User-based prompts: correspond to a specific use-case that was requested for the OpenAI API.

The paper [38] describes the main three ways that prompts request information.

1. Direct: "Tell me about..."
2. Few-shot: Given these two examples of a story, write another story about the same topic.
3. Continuation: Given the start of a story, finish it.

The users questions and expert responses resulted in 13,000 input/output dataset on which GPT-3 is tuned by supervised training.

3.1.2 Reward Model

After the SFT model is trained using the training dataset generated by human experts, the model generates better-aligned responses to user prompts. The next improvement in the model is achieved by specifying a reward value for responding in a particular way. This methodology is incorporated to enforce a specific way of response among several options for a given question.

To train the reward model, experts are presented with 4 to 9 SFT model outputs for a single input prompt. They are asked to rank these outputs from best to worst, creating combinations of output ranking as shown in Fig 5

Collect comparison data and train a reward model.

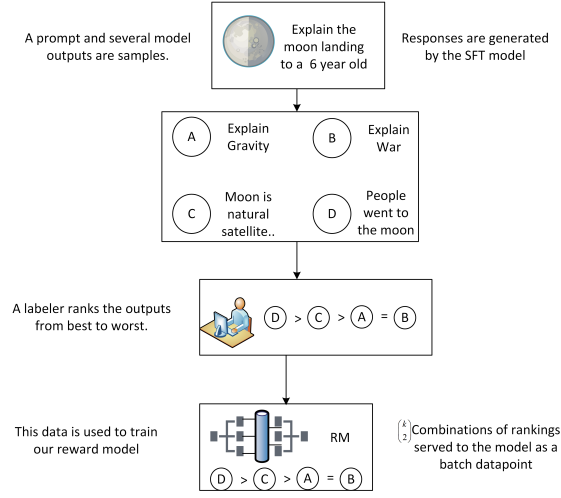


Figure 5: Reward Model

Optimize a policy against the reward model using reinforcement learning

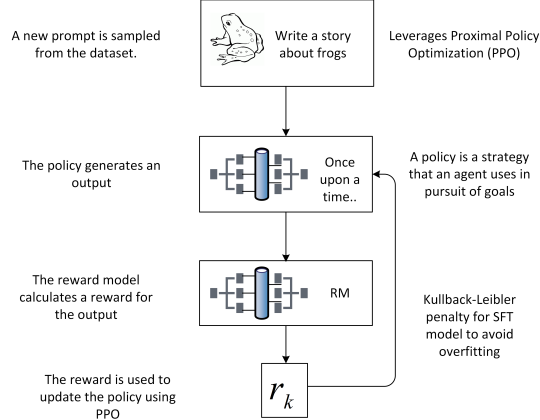


Figure 6: Reinforcement Learning Model

3.1.3 Reinforcement Learning Model

In the final stage, the model is presented with a random prompt and returns a response. The response is generated using the ‘policy’ that the model has learned in step 2. The policy represents a strategy that the machine has learned to use to achieve its goal; in this case, maximizing its reward. Based on the reward model developed in step 2, a scalar reward value is then determined for the prompt and response pair. The reward then feeds back into the model to evolve the policy as shown in Fig 6. In 2017, Schulman et al. [39] introduced Proximal Policy Optimization (PPO), the methodology that is used in updating the model’s policy as each response is generated. PPO incorporates a per-token Kullback–Leibler (KL) penalty from the SFT model. The KL divergence measures the similarity between two probability distributions and in this case penalizes extreme distances.

Using a KL penalty reduces the distance that the responses can be from the SFT model outputs trained in step 1 to avoid over-optimizing the reward model and deviating too drastically from the human intention dataset.

3.1.4 Evaluation of the Model

Evaluation of the model is performed by setting aside a test set during training that the model has not seen. On the test set, a series of evaluations are conducted to determine if the model is better aligned than its predecessor, GPT-3.

1. Helpfulness: It is the model’s ability to infer and follow user instructions. Labelers preferred outputs from InstructGPT over GPT-3 $85 \pm 3\%$ of the time.
2. Truthfulness: It is the model’s tendency for hallucinations. The PPO model produced outputs that showed minor increases in truthfulness and informativeness when assessed using the TruthfulQA dataset.
3. Harmlessness: It is the model’s ability to avoid inappropriate, derogatory, and denigrating content. Harmlessness was tested using the RealToxicityPrompts dataset. The test was performed under three conditions.
 - (a) Instructed to provide respectful responses: resulted in a significant decrease in toxic responses.
 - (b) Instructed to provide responses, without any setting for respectfulness: no significant change in toxicity.
 - (c) Instructed to provide toxic response: responses were in fact significantly more toxic than the GPT-3 model.

4 Impact on Teaching Computer Science and allied engineering streams

In spite of the ability to synthesize text, ChatGPT demonstrated a remarkably high quality of computer programs, when prompted with a problem statement. This led to the thought of using ChatGPT for teaching computer science and cybersecurity applications.

4.1 Impact on Teaching Computer Science

Hazzan [40] listed several avenues for incorporating ChatGPT as a tool for enhancing pupils’ skills by expanding their knowledge through ChatGPT’s answers, fostering their ability to ask questions and to formulate them precisely, and imparting skills to determine the correctness, quality and reliability of ChatGPT’s answers, as well as to filter the relevant information received from these answers.

Here are examples of how ChatGPT could be used in computer science education:

1. Give ChatGPT a programming task and ask the students to explain it. Explain what is the approach used by ChatGPT and/or the results generated by ChatGPT.
2. Give ChatGPT a programming task and analyze its answer together with the students: Some of the deliberations that can be done with students are the following. Is it correct? How can we check its correctness? Is it readable? Is it efficient? What is its complexity? Does the program work for any and all inputs? How can we test it? Can it be improved?
3. Compare ChatGPT’s answer to a task with the students’ own solutions; identify and explain the similarities, and identify and explain the differences.
4. Give ChatGPT a problem statement. Ask it to generate/develop an algorithm to solve the problem, and to analyze the correctness, and computational complexity of its solution.
5. For the same problem above, ask ChatGPT to generate multiple algorithms to solve the same problem. Ask ChatGPT analyze the correctness and computational complexity of each of the algorithms it generated. Ask ChatGPT to compare and contrast each of its solutions, and provide a critique of each solution. Ask the students to do the same on the algorithms ChatGPT generated.
6. Submit a problem statement and a solution to ChatGPT. Ask ChatGPT to critique the solution. Students can use this to get insights on how to improve their work.

The task of website development has been reported to be semi-automatic in [41]. Several other examples are also there where ChatGPT generated Java script to populate a website with HTML code and CSS code for alignment.

An attempt to obtain the output of a C program using ChatGPT provides following output.

Prompt: What is the output of the program:

```
int main()
{
    int a[4][5]={1,2,3,4,5},
    {6,7,8,9,10},
    {11,12,13,14,15},
    {16,17,18,19,20}};
    printf("%d\n", *((a+**a+2)+3));

    return 0;
}
```

"The output of the program is 14.

Here's how the code works:

1. The array 'a' is initialized as a 4x5 matrix with values from 1 to 20.
2. The expression '**a' evaluates to the first element of the first row of the array, which is 1.
3. The expression 'a+**a+2' points to the third row of the array.
4. The expression '*(a+**a+2)+3' points to the fourth element of the third row of the array, which is 14.
5. The outermost '*' dereferences this pointer and returns the value 14.
6. The 'printf' statement prints the value 14."

The correct output is 19 instead of 14. However, the explanation is correct.

4.2 Impact on Teaching Network Programming and Cybersecurity

ChatGPT generated a working script for configuring Cisco Switches in [42]. There are several variations of the script presented by ChatGPT for trial. The learner can have a repository of working scripts and evaluate any potential bugs in the process. The learner is only required to focus on the logic of the script and need not memorize all the commands in the script.

The embedding of AI in cybersecurity yields promising results. Several applications of ChatGPT in cybersecurity can be listed as follows [43]

1. Breach reports: A SOAR [44] can collect all cyber incidents and supporting data together and synthesize a severity level and timeline of events to ChatGPT. ChatGPT can generate a draft breach report to be reviewed by an analyst before distribution.
2. ChatGPT can create a short executive summary of the main findings and remedial actions from long compliance report generated by SOAR.
3. Awareness training: The ChatGPT SOAR integration can automate part of the awareness training. ChatGPT automatically generates phishing emails, and the SOAR playbook extracts data from LinkedIn, enriches it with email addresses and connections from past logs, and sends the phishing email to selected recipients, measuring how many clicks through and how many alerts the phishing response team.

4.3 Impact on Teaching AI and Data Science

Artificial intelligence (AI) and Data Science (DS) are emerging subjects that can use extensive ChatGPT responses for curriculum development and instruction. ChatGPT can generate quick notes on different AI topics like Deep Neural Networks, Reinforcement Learning, LSTM, GRU, and Ensemble-based learning,

learning paradigms (e.g., supervised, unsupervised, self-supervised, few-shot, and active learning), transfer learning/ domain adaptation, etc. Complexity analysis of a particular AI method can be deciphered using ChatGPT. The judgment of the appropriate technique for solving a given problem can be enquired from ChatGPT. A sample implementation can also be sought from ChatGPT provided that some physical constraints may be respected in the implementation. Physics Informed Neural Networks (PINN) is also another spectrum of AI where ChatGPT may find innovative applications. Either replicating a differential equation or respecting the limits of an algebraic equation, ChatGPT may assist in formulating the solution theme, if not entirely an acceptable solution. Hardware accelerated implementation of AI, particularly in GPU is of interest to the developers in using ChatGPT responses.

Along these lines, ChatGPT can also be used to generate initial results for an AI/machine learning problem, which can then be expanded upon, and then refined to develop a final solution. An example instance of this would in be using ChatGPT to generate initial values for the various weights and hyper-parameters involved in a given deep learning solution. These can then be improved with further refinement steps. Such refinement steps could even involve a possible iterative use of ChatGPT itself. Students can be engaged at any step in this iterative process, from the generating the initial results/solutions to the refinement steps.

Data Science is another computationally intensive application suitable for ChatGPT inference.

As described in [45], Data Science involves the capture, maintenance, processing, analysis, and communication of data to different stakeholders. The stages of processing and analysis in DS are more likely to find immediate leverage of the predictive capability of ChatGPT, though ChatGPT could also be applied to other stages. For instance, for applications in business intelligence, ChatGPT could suggest the most appropriate metric to be computed which may be of interest to a sales team while other suitable statistics for R&D experts and some other measures for the Global Strategies group. Big Data processing using Apache Spark or Hadoop may also use ChatGPT for testing prototype code and improving on it for specialized requirements during a project cycle.

A query related to a theoretical objective question provides the following result.

Prompt: Which of the following is an example of unsupervised neural network?

- A. Back-propagation network
- B. Hebb network
- C. Associative memory network
- D. Self-organizing feature map

"D. Self-organizing feature map (SOFM) is an example of an unsupervised neural network. SOFM, also known as Kohonen network, is a type of artificial neural network that is trained on an unsupervised learning method where the network learns to identify patterns in the input data without any labeled output. It is commonly used for clustering and visualizing high-dimensional data by reducing it to a lower-dimensional representation.

- A) Back-propagation network is an example of a supervised neural network, where the network learns from labeled input-output pairs during training.
- B) Hebb network is a type of unsupervised neural network, but it is not commonly used to day due to its limitations and lack of applicability to real-world problems.
- C) Associative memory network is a type of neural network that is used to store and retrieve patterns or memories, but it is not strictly an unsupervised neural network as it can also be trained in a supervised or reinforcement learning framework."

This example demonstrates that ChatGPT provides the correct response and backs its claim with profound reasons.

4.4 Impact on Teaching Electrical Engineering

On first impression, electrical engineering education may not appear to be a fertile ground for applying ChatGPT, as there are typically small training data sets available in this field. The combination of theoretical understanding and its application in solving electrical engineering problems requires a high level of cognitive thinking. However, we can still identify some interesting applications of ChatGPT in this domain.

Here, we show some snapshots on the queries posed to ChatGPT related to Electrical Engineering, and the respective responses from ChatGPT. We also comment on some of these as needed.

A query related to Linear Time Invariant System produces the following output.

Prompt: What is Linear time invariant system?

"Linear Time-Invariant (LTI) systems are mathematical models that describe the behavior of physical systems, such as electrical circuits, mechanical systems, or biological systems. An LTI system has the following properties:

1. Linearity: The system response is proportional to the input, which means that if you have two inputs, the output is just the sum of the responses to each input.
2. Time-invariance: The system response does not change over time, which means that if you apply the same input signal at two different times, you will get the same response.
3. Causality: The system response depends only on past and present inputs and not on future inputs. These properties allow us to use linear algebra and Fourier analysis to study the behavior of LTI systems and design control systems that can stabilize or modify the behavior of these systems."

The response precisely starts with the context of LTI system which is a mathematical representation of different physical systems. The response follows by correctly defining the two aspects of the LTI system, which are linearity and time-invariance. ChatGPT could add additive and homogenous for the system to follow superposition and hence, linearity to enrich the quality of the result. Though, it has also mentioned causality.

A query on the doping of the Zener diode produces the output below.

Prompt: Which junction of zener diode is heavily doped?

"The heavily doped junction in a Zener diode is the p-type side, also known as the anode side. The heavy doping allows the p-type material to exhibit a large number of charge carriers, making it easier for the diode to operate in reverse breakdown mode. In reverse breakdown mode, the diode allows a large current to flow in the reverse direction, maintaining a constant voltage drop across the diode, which is characteristic of Zener diodes."

ChatGPT fails to answer that both P-N is heavily doped. However, the rest of the reasoning looks correct.

A query on the output response of a given LTI system produces the following output

Prompt: A system having transfer function $G(s)=(1-s)/(1+s)$. A unit step input is applied at time $t=0$. What is the value of the response of the system at $t=1.5$ sec?

"The transfer function ' $G(s) = (1 - s) / (1 + s)$ ' describes the relationship between the Laplace Transform ' $X(s)$ ' of the input ' $x(t)$ ' and the Laplace Transform ' $Y(s)$ ' of the output ' $y(t)$ ' of the system. When a unit step input ' $u(t)$ ' is applied at time ' $t = 0$ ', the input ' $x(t)$ ' can be represented as ' $x(t) = u(t)$ '. To find the response of the system at ' $t = 1.5$ sec', we need to find the inverse Laplace Transform of the transfer function ' $G(s)$ ' and evaluate it at ' $t = 1.5$ sec'. To find the inverse Laplace Transform of ' $G(s)$ ', we can use partial fraction expansion and then use tables of Laplace Transform pairs to find the inverse Laplace Transform. The inverse Laplace Transform of ' $G(s)$ ' can be represented as:

$$g(t) = L^{-1}\{G(s)\} = (1/2) * e^{-t} - (1/2) * e^{+t} \quad (1)$$

So, when ' $t = 1.5$ sec', the value of the response of the system is:

$$g(1.5) = (1/2) * e^{-1.5} - (1/2) * e^{+1.5} \quad (2)$$

Evaluating this expression using a calculator, we get ' $g(1.5) = -0.0753$ '. So, the value of the response of the system at ' $t = 1.5$ sec' is approximately equal to ' -0.0753 '."

A computationally intensive question on induction motor results in the following output.

Prompt: A 4 pole induction machine is working as an induction generator. The generator

supply frequency is 60 Hz. The rotor current frequency is 5 Hz. What is the mechanical speed of the rotor in RPM?

"The mechanical speed of the rotor in RPM can be calculated using the equation:

$$N = (f_g - s * f_r) / p \quad (3)$$

where:

1. N is the mechanical speed of the rotor in RPM
2. f_g is the generator supply frequency in Hz
3. f_r is the rotor current frequency in Hz
4. s is the slip, which is the difference between the synchronous speed (N_s) and the mechanical speed of the rotor, expressed as a fraction of the synchronous speed
5. p is the number of poles in the machine

The synchronous speed of a 4-pole machine can be calculated as:

$$N_s = (120 * f_g) / p \quad (4)$$

Substituting the values for f_g and p , we get:

$$N_s = (120 * 60) / 4 = 1800 \text{ RPM} \quad (5)$$

The slip can be calculated as:

$$s = (N_s - N) / N_s \quad (6)$$

Substituting the values for N_s and f_r , we get:

$s = (1800 - N) / 1800 = (1800 - N) / 1800 = (1800 - N) / 1800 = (1800 - N) / 1800 = (1800 - N) / 1800 = (1800 - N) / 1800 = (1800 - 5) / 1800 = 1795 / 1800$

Finally, substituting the values for N_s , f_r , s , and p into the equation for N , we get:

$N = (60 - (1795 / 1800) * 5) / 4 = (60 - 4.975) / 4 = 55.025 / 4 = 13.756 \text{ RPM}$

So the mechanical speed of the rotor is approximately 13.76 RPM."

On indicating that the generator speed should be more than the synchronous speed, ChatGPT politely accepts the error and attempts to synthesize another set of responses which is also not correct. A part of the reattempt is shown here.

Prompt: Generator speed should be more than synchronous speed.

I apologize, you are correct. The generator speed should be greater than the synchronous speed for an induction generator. In this case, the synchronous speed is 1800 RPM, so the generator speed should be greater than that. However, the calculation above resulted in a value less than the synchronous speed, which is incorrect.

Embedded programming requires a high degree of physical system understanding, relevant context, and a lot of documentation reading. People have tried to generate embedded code for SPI interface with DMA access and interrupt [46], but simply not suitable to run as it is in a microcontroller. Similar reports are also available for FPGA programming where ChatGPT generated non-functional Verilog[47, 48].

One key challenge here is that there are not enough public RTL datasets available for ChatGPT to produce acceptable code.

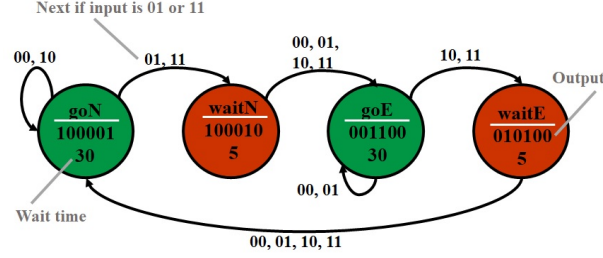


Figure 7: State transition graph (STG) for Traffic Light.

Current state	Output	Next State Based on Input			
		Input 00	Input 01	Input 10	Input 11
GoN	100001	goN	waitE	goN	waitE
WaitN	100010	goE	goE	goE	goE
GoE	001100	goE	goE	waitE	waitE
WaitE	010100	goN	goN	goN	goN

Table 1: Correct state transition table (STT) generated by help of ChatGPT.

4.5 Impact on teaching Robotics Systems

This study aimed to illustrate how students could leverage ChatGPT to comprehend the problem statement and assist them in resolving intricate problems by utilizing an indirect approach. To that end, we utilized the Texas Instruments (TI) Robotics Systems Learning Kit, an economical robotics kit and classroom curriculum designed to augment students' understanding of embedded system designs by covering the fundamentals of embedded systems and progressing to more complex application learning. In this evaluation, students were presented with three questions concerning the design of a traffic light system for both following line robot and pedestrians. The first question was to draw a state transition table (STT) for the state transition diagram in Fig. 7 using ChatGPT. Fig. 7 demonstrated a state transition graph (STG) of finite state machine (FSM) that controls a traffic light intersection with two directions. In order to obtain precision response, students need to first identify the inputs and outputs of the system such as care sensors in each direction and traffic lights, respectively. Next, students would need to identify the states of the system where four state: "goN" for going to the north, "waitN" for waiting on the north, "goE" for going to the east, and "waitE" for waiting on the east. So, the input/prompt for ChatGPT should be "draw a state transition table for the following state transition diagram: first state is goN where if the input is 00 or 10 it remains in that state but if the input is 01 or 11 it goes to the next state called waitN. The state waitN has all possible inputs 00, 01, 10, 11 go to the next state called waitE. The state goE remains in goE if the inputs are 00 or 01 and moves to the last state called waitE if the inputs are 10 or 11. The state waitE returns to the first state goN for all possible inputs 00, 01, 10, 11" to generate STT 1.

Next question was to explain index into array data structure in C code for controlling traffic lights at an intersection using FSM. As can be seen in Fig.8, the C code was given to ChatGPT to explain the code. It's notable that ChatGPT's response accurately describes the behavior of the code. Indeed, while C code did not explicitly mention the context of the code controlling traffic lights at an intersection, ChatGPT's response was able to accurately interpret and explain the functionality of the FSM based on the provided code. Here is the response from ChatGPT:

"This code implements a finite state machine (FSM) for controlling traffic lights at an intersection. The intersection has two directions of traffic, north-south and east-west. The FSM has four states: goN, waitN, goE, and waitE, which correspond to the states where the north-south traffic has a green light and the east-west traffic has a red light, the north-south traffic has a yellow light and the east-west traffic has a red light, the east-west traffic has a green light and the north-south traffic has a red light, and the east-west traffic has a yellow light and the north-south traffic has a red light, respectively. The FSM is implemented as an array of four constant structures of type *State_t*, where each structure represents a state in the FSM. Each structure has three fields:

- Out: a 6-bit output value that controls the traffic lights. The least significant two bits control the north-south lights, and the next two bits control the east-

```

const struct State {
    uint32_t Out;    // 6-bit output
    uint32_t Time;   // 1 ms units
    uint32_t Next[4]; // list of next states
};
typedef const struct State State_t;

#define goN 0
#define waitN 1
#define goE 2
#define waitE 3
State_t FSM[4] = {
    {0x21, 30000, {goN,waitN,goN,waitN}},
    {0x22, 5000, {goE,goE,goE,goE}},
    {0x0C, 30000, {goE,goE,waitE,waitE}},
    {0x14, 5000, {goN,goN,goN,goN}}
};

```

Figure 8: Index into array data structure in C code for controlling traffic lights at an intersection using FSM.

west lights. Bit 5 is reserved for future use. Bit 4 controls a pedestrian crossing signal for the north-south direction, and bit 3 controls a pedestrian crossing signal for the east-west direction.

- Time: a time duration in milliseconds that the FSM should wait in this state before transitioning to the next state.
- Next: an array of four indices into the FSM array that specify the next state to transition to depending on the input from car sensors. The four indices correspond to the input values 0, 1, 2, and 3, where input 0 means no cars detected, input 1 means cars detected in the north-south direction only, input 2 means cars detected in the east-west direction only, and input 3 means cars detected in both directions."

The first two questions aimed to help students understand state transition graphs (STGs) and state transition tables (STTs), respectively. The third question asked students to write C code for another STG, similar to the code given in question 2. Based on Fig. 9, students should write a index into array data structure C code to implement the line tracker robot to detect the contrast between the line and the surface in which, the robot can determine whether it is on the line or off it and make adjustments to stay on the line. Based on STG in Fig. 9, the input variable represents the sensor input from the line tracker sensor, with 00 indicating that the robot is not on the line, 01 indicating that it is on the right side of the line, 10 indicating that it is on the left side of the line, and 11 indicating that it is directly on the line. The Output variable represents the robot's movement output, with 3 indicating that the robot should move straight, 2 indicating that it should turn right, and 1 indicating that it should turn left. The FSM transitions between the Center, Left, and Right states based on the Input value and sets the motor output based on the Output value. This allows the robot to follow the line by making adjustments to its movement based on the sensor input. It's important for students to have a solid understanding of the problem and the requirements in order to provide the necessary input and describe the problem effectively to ChatGPT. Providing clear and detailed input will help ensure that the code generated by ChatGPT is accurate and meets the requirements of the problem. Additionally, having a deep understanding of the problem will also help students in debugging and modifying the generated code as needed. As can be demonstrated in Fig. 10, the C codes for implementing line tracker robot using STG for both generated by ChatGPT and Original solution are quite similar.

5 Path Forward

5.1 Integrating into computing and engineering education

There is a promising application for integrating ChatGPT in teaching Computer Science and Engineering subjects. Considering the present capability of ChatGPT, it can be successfully used for designing alternate methodology, debugging, complexity analysis, and understanding concepts. However, for electrical engineering, the scope is still limited to practicing theoretical questions and generating quiz problems for practice. Much

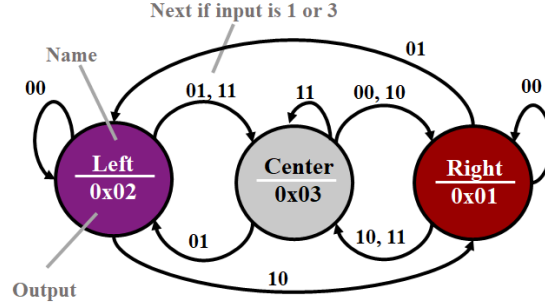


Figure 9: State transition graph for simple line tracker robot using an FSM with 3 states: Center, Left, and Right.

```

#define NUM_STATES 3
#define NUM_INPUTS 4

typedef struct {
    uint32_t out;
    uint32_t delay;
    uint8_t next[NUM_INPUTS];
} State;

State fsm[NUM_STATES] = {
    {0x03, 50, {2, 1, 2, 0}}, // Center
    {0x02, 50, {1, 0, 2, 0}}, // Left
    {0x01, 50, {2, 1, 0, 0}}  // Right
};

```

(a)

```

struct State {
    uint32_t out;           // 2-bit output
    uint32_t delay;         // time to delay in 1ms
    const struct State *next[4]; // Next if 2-bit input is 0-3
};

typedef const struct State State_t;

#define Center &fsm[0]
#define Left &fsm[1]
#define Right &fsm[2]

State_t fsm[3] = {
    {0x03, 50, { Right, Left, Right, Center }}, // Center
    {0x02, 50, { Left, Center, Right, Center }}, // Left
    {0x01, 50, { Right, Left, Center, Center }} // Right
};

```

(b)

Figure 10: The C codes for implementing line tracker robot using STG. (a) C code generated by ChatGPT, (b) original solution of this question.

more work is certainly required in identifying appropriate ways to use ChatGPT to improve electrical engineering education. The future release of ChatGPT which will be trained on approximately 170 Trillion parameters is expected to deliver promising results on the present shortcomings.

5.2 Identifying Student's work Prepared by ChatGPT

With the emergence of ChatGPT and other similar AI-based text generators/tools, an important new challenge becomes how to determine when a given text or part thereof is generated using an AI tool. Another is the question of copyrights and attribution for such AI-generated materials.

Currently, one possible way to check ChatGPT generated text is to consider references and how generic the material is. For example, ChatGPT does not provide any embedded references. That is a quick giveaway that the text was generated by one of the regenerative AI systems. We should allow the students to use this technology as a starting point. Then they have to edit the essay by discovering contemporary references and embedding them in the text and suitably altering it to make sense. When asked for references during one session, ChatGPT gave a list of ten out of which seven did not exist!

We should also insist on the honor system that students highlight their contributions. Some other systems such as ChatSonic, which integrate Google search results may also be presented [49].

AI-generated text checkers already exist. For example, GPTZero [50] detects the probability of a text generated by AI for even mixed AI-human generated texts.

5.3 Plagiarism and Ethics

Plagiarism detection systems such as Turnitin are gearing up for dealing with the negative aspects of ChatGPT and other similar AI tools [51, 52].

ChatGPT itself responds with a very balanced answer when prompted about the ethics of using ChatGPT by a student:

Prompt: Is using ChatGPT ethical for a student?

"Whether using chatgpt (or any other AI technology) is ethical for a student depends on the context and the specific situation. Here are some things to consider:

1. Academic integrity: If the student is using chatgpt to generate original work that they will present as their own, such as essays or research papers, this could be considered a violation of academic integrity. Students are typically expected to produce original work and to properly cite any sources used in their assignments.
2. Purpose of the assignment: If the assignment is designed to test the student's ability to synthesize information, analyze data, or engage in critical thinking, using chatgpt may not be an ethical option. On the other hand, if the assignment is designed to help the student learn about the capabilities and limitations of AI technology, using chatgpt could be considered ethical.
3. Understanding and learning: If the student is using chatgpt to generate work that they will use as a starting point for their own further analysis and understanding, this could be considered ethical. However, it is important that the student thoroughly understands and critically evaluates the work produced by chatgpt, and that they are able to explain the reasoning and thought process behind any conclusions or insights."

In general, using ChatGPT or any other AI technology ethically in a student context requires being mindful of the purpose and goals of the assignment, as well as maintaining academic integrity and ensuring that the student has a deep understanding of the work produced by the technology. It is imperative that the students or the scholars voluntarily declare that the text submitted by the individual is assisted by ChatGPT or any AI tool. Withholding such information may lead to an actionable consequence if such an instance is found at a later stage while evaluating a scholarly work.

5.4 Rethinking Learning Assessment

The availability of a scientific calculator was frowned upon by similar apprehensions from the teaching community that the students will find the laws of integration redundant. This proved negligibly correct as fresh problems require sophisticated transformation prior to applying definite integrals in computing systems. The transition of Math assignments from compute-intensive tasks to more understanding took place with the availability of calculators. The questions in Chemistry evolved from memorizing elements in the Periodic Table to the possible feasibility of certain reactions. The assessment for financial accounts changed from bookkeeping exercises to tax fraud identification. In similar thoughts, several subjects will see a transformation for academic evaluation with more infiltration of generative AI in our daily life. The high school admission essay may witness a major transformation, especially in the way it is evaluated. We envisage that ChatGPT and generative AI will lead to modifying the curriculum in courses that require rote learning (be it in engineering, humanities, or the social sciences), with significant transformational impact. Evaluators need to think that if a bot can solve their questions, then why pose them to humans? The reward for critical thinking will be even more with generative AI around us. In April 1966, Feynman delivered an address to the National Science Teachers Association, in which he suggested how students could be made to think like scientists, be open-minded, curious, and especially, to doubt. As Willis et al. opined [53], learning is most appropriate using challenges. ChatGPT will occupy a pivotal role in providing such challenges.

6 Summary

With the rise of ChatGPT and the expected impact on education, we need to evaluate our educational offerings and assessment process. Educational tools need to start emphasizing the process of learning over

the outcome. Authors believe that AI still can't match human intelligence in terms of accuracy, creativity, or originality. We should neither fear nor overestimate ChatGPT's impact. Rather, we should embrace it and exploit it to its fullest to improve our existing processes in education (teaching, learning, and assessment).

Like social media, the internet, and the calculator that all came before it, the impact of ChatGPT and similar AI technologies will be enormous and will be felt by students, teachers, administrators, and governments alike. This will come with both significant advantages and pitfalls. We must find ways to harness these advantages while developing "guardrails" and approaches to mitigate their downsides.

7 ACKNOWLEDGMENTS

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