# Bot or Human? Detecting ChatGPT Imposters with A Single Question

# Hong Wang<sup>†</sup>, Xuan Luo<sup>‡</sup>, Weizhi Wang<sup>†</sup>, Xifeng Yan<sup>†</sup>

University of California Santa Barbara<sup>†</sup>, Xi'an Jiaotong University<sup>‡</sup> {hongwang600,weizhiwang,xifeng}@ucsb.edu, luoxuan.cs@gmail.com

## **Abstract**

Large language models like ChatGPT have recently demonstrated impressive capabilities in natural language understanding and generation, enabling various applications including translation, essay writing, and chit-chatting. However, there is a concern that they can be misused for malicious purposes, such as fraud or denialof-service attacks. Therefore, it is crucial to develop methods for detecting whether the party involved in a conversation is a bot or a human. In this paper, we propose a framework named FLAIR, Finding Large Language Model Authenticity via a Single Inquiry and Response, to detect conversational bots in an online manner. Specifically, we target a single question scenario that can effectively differentiate human users from bots. The questions are divided into two categories: those that are easy for humans but difficult for bots (e.g., counting, substitution, positioning, noise filtering, and ASCII art), and those that are easy for bots but difficult for humans (e.g., memorization and computation). Our approach shows different strengths of these questions in their effectiveness, providing a new way for online service providers to protect themselves against nefarious activities and ensure that they are serving real users. We open-sourced our dataset on https://github. com/hongwang600/FLAIR and welcome contributions from the community to enrich such detection datasets.

# 1 Introduction

Recently, the development of Large Language Models (LLMs) such as GPT-3 [Brown et al., 2020], PaLM [Chowdhery et al., 2022], and ChatGPT [OpenAI, 2022] has brought significant advances in natural language processing, enabling superior performance in downstream tasks such as language understanding [Smith et al., 2022, Chowdhery et al., 2022], question answering [Su et al., 2019a, Liang et al., 2022], and dialogue systems [Wang et al., 2022b, Qian and Yan, 2023]. These models have shown remarkable abilities in understanding and generating human-like language, providing benefits across various domains, including healthcare, education, finance, and entertainment. With their ability to learn from massive amounts of data, these models are constantly improving and becoming more versatile, paving the way for new and exciting applications.

However, with the proliferation of these models, concerns have emerged regarding their potential misuse for malicious purposes. One of the most significant threats is the use of large language models to impersonate human users and engage in nefarious activities, such as fraud, spamming, or denial-of-service attacks. For instance, ChatGPT agents could be used by hackers to occupy all customer service channels of various corporations, such as e-commerce, airlines, and banks. Moreover, with the help of text-to-speech (TTS) techniques, machine-generated voices could even occupy public service lines like 911, leading to severe public crises [Wang et al., 2021]. These attacks could cause significant harm to online service providers and their users, eroding the trust and integrity of online interactions.

Differentiating between human users and malicious bots is a long-standing topic of interest for both industry and academia. Conventional techniques, such as the use of CAPTCHAs [Von Ahn et al., 2003], have been developed to determine whether a user is a human or a bot in order to prevent bot spamming and raiding. A commonly used CAPTCHA method involves asking users to recognize distorted letters and digits. However, these approaches face significant challenges when it comes to detecting chatbots involving text and voice only. This is where the emergence of large language models such as GPT-3 and ChatGPT has further complicated the problem of chatbot detection, as they are capable of generating high-quality human-like text and mimicking human behavior to a considerable extent. Although recent studies such as DetectGPT have proposed methods to classify if text is generated by ChatGPT or not, they focus on the offline setting. A recent study [Sadasivan et al., 2023b] shows that these detectors are not reliable under paraphrasing attacks, where a light paraphraser is applied on top of the generative text model. This limitation highlights the need for more robust and accurate methods to differentiate large language models from human users and detect their presence in online chat interactions.

	Humans good at	Humans not good at
Bots good at	×	memorization computation
Bots not good at	symbolic manipulation noise filtering √ randomness graphical understanding	×

Table 1: Leveraging tasks that Bots and Humans are (not) good at

In this paper, we propose a novel framework named FLAIR, Finding LLM Authenticity with a Single Inquiry and Response, to take full advantage of the strength and weakness of LLMs for LLM-based conversational bot detection. Specifically, we introduce a set of carefully designed questions that induce distinct responses between bots and humans. These questions are tailored to exploit the differences in the way that bots and humans process and generate language. As shown in Table 1, certain questions in the fields of symbolic manipulation, noise filtering, and graphical understanding are difficult for bots but relatively easy for humans. Examples include the counting, substitution, positioning, noise injection, and ASCII art. On the other hand, memorization and computation was relatively easy for bots but difficult for humans. Specifically, counting requires users to count the number of times a particular character appears in a string. Substitution involves substituting the characters of a random string according to a given rule. In positioning, users are asked to identify the k-th character after the j-th appearance of a given character c in a random string. Random editing involves performing random operations, such as dropping, inserting, swapping, and substituting characters, on a randomly generated string and producing three distinct outputs. Noise injection presents common-sense questions that have been modified with additional characters. ASCII art require users to identify what is being depicted by ASCII characters. Memorization asks questions that demand the enumeration of items within a category or domain-specific knowledge that are challenging for humans to recall. Computation requires users to provide answers to complex math questions, such as calculating the product of two randomly sampled four-digit numbers. Our experimental results demonstrate that FLAIR is effective in practice and offers a viable alternative to traditional CAPTCHAs. The proposed approach shows promise in developing more robust and accurate methods to detect bots quickly and protect online interactions.

The rest of the paper is organized as follows. Section 2 shows some related work in this field. Sections 3 and 4 present our proposed approaches to detect LLMs by leveraging their weaknesses and strengths respectively. Section 5 shows the experimental results. Finally, Section 6 concludes the paper.

#### 2 Related Works

# 2.1 CAPTCHAs

CAPTCHA [Von Ahn et al., 2003] is a common technique used to block malicious applications like dictionary attacks, E-mail spamming, web crawlers, phishing attacks, etc. There are different types

of CAPTCHAs. Text-Based CAPTCHAs require the users to recognize letters and digits in distortion form [Chew and Baird, 2003, Mori and Malik, 2003, Yan and El Ahmad, 2008], while Image-Based CAPTCHAs [Gossweiler et al., 2009] require users to choose images that have similar properties such as traffic lights. Video-Based CAPTCHAs [Kluever, 2008] require the user to choose three words that describe a video, and Audio-Based CAPTCHAs [Gao et al., 2010] ask the user to listen to an audio and submit the mentioned word [Saini and Bala, 2013]. Puzzle CAPTCHAs [Singh and Pal, 2014] require the user to combine segments to form a complete picture. These techniques are used to differentiate between human users and bots, preventing malicious activities.

## 2.2 Large Language Models

The emergence of Large Language Models significantly advances the state-of-the-art (SOTA) for NLP tasks and benchmarks. Enabled by the paradigm of large-scale self-supervised pre-training and task-specific tuning, the early LLMs [Devlin et al., 2018, Liu et al., 2019, Lewis et al., 2019, Radford et al., 2018, 2019, Raffel et al., 2020] demonstrate incredible capability in resolving multiple downstream tasks like text classification, natural language inference, machine translation, reading comprehension, etc. Additionally, via fusing multimodal knowledge like tables, images, and graphs into language modeling process, LLMs have been endowed with the ability to handle multimodal tasks beyond text, including entity typing [Zhang et al., 2019], node classification [Zhang et al., 2020], visual question-answering [Su et al., 2019b], multimodal commonsense reasoning [Wang et al., 2022a], etc. Furthermore, through the scaling up on both model parameters and context length, LLMs like GPT-3 [Brown et al., 2020] can even work as few-shot learners and resolve unseen tasks via in-context learning with several demonstrations. Then, to further facilitate LLMs to follow a user's intent, InstructGPT [Ouyang et al., 2022] is proposed to aligning LLMs with human intent instructions via deep reinforcement learning on human feedback. Later, ChatGPT [OpenAI, 2022] and GPT-4 [OpenAI, 2023b], as latest variants of InstructGPT, ignites the enthusiasm of AI-Generated-Content (AIGC). Through collaboration with vector databases and plugin tools [OpenAI, 2023a], GPT-4 currently supports thousands of downstream applications.

## 2.3 ChatGPT offline detection

Since its introduction, ChatGPT has become widely used and raised public concerns about potential misuse. For instance, students may use ChatGPT to complete written assignments, making it difficult for instructors to accurately assess student learning. As a result, there is a growing need to detect whether a piece of text was written by ChatGPT. To tackle this problem, DetectGPT [Mitchell et al., 2023] proposes a solution by comparing the log probabilities of the original passage with that of the perturbations of the same passage. The hypothesis behind this method is that minor rewrites of text generated by the model would likely result in lower log probabilities compared to the original sample, while minor rewrites of text written by humans may result in either higher or lower log probabilities. Another line of study model this problem as binary classification problem and fine-tune another model using supervised data [Bakhtin et al., 2019]. Most recently, Mitrović et al. [2023] fine-tunes a Transformer-based model and uses it to make predictions, which are then explained using SHAP [Lundberg and Lee, 2017]. Another area of research focuses on adding watermarks to AI-generated text in order to facilitate their identification, which involves imprinting specific patterns on the text to make it easier to detect [Zhao et al., 2023]. Soft watermarking, as proposed by Kirchenbauer et al. [2023], involves dividing tokens into green and red lists in order to create these patterns. When generating text, a watermarked LLM is more likely to select a token from the green list, which is determined by the prefix token. These watermarks are often subtle and difficult for humans to notice.

However, as demonstrated in Sadasivan et al. [2023a], a range of detection methods, including watermarking schemes, neural network-based detectors, and zero-shot classifiers, can be easily defeated by paraphrasing attacks. These attacks involve applying a light paraphraser to text generated by a language model. Furthermore, a theoretical analysis suggests that even the best possible detector can only perform marginally better than a random classifier when dealing with a sufficiently good language model. This highlights the fundamental challenge in offline detection of text generated by advanced language models, which can produce writing that is virtually indistinguishable from human-written text. Thus, it is more meaningful and crucial to shift the focus to online detection settings where users engage in live chat interactions with the system.

In the following discussion, we will present our FLAIR framework for detecting Large Language Models, such as ChatGPT, in an online setting where users engage in real-time conversations with the system. Our method involves asking users questions and distinguish bots from humans based on the correctness of their answers. We have categorized the FLAIRs into two types. The first type includes questions that are difficult for LLMs but easy for humans. These types of questions typically require skills such as symbolic manipulation, noise filtering, and graphical understanding, which are not strong points of LLMs Qian et al. [2022]. It is possible to bypass these tests by fine-tuning LLMs with failed testing cases or using plug-ins of specific routines. We argue that these tests show the fundamental weaknesses inside LLMs. The second type includes questions that are easy for LLMs but difficult for humans. These questions typically require memorization and computation, which is not a strong suit of humans. In the following sections, we will discuss each of them in detail.

# 3 Leveraging the Weakness of LLM

## 3.1 Counting

State-of-the-art LLMs cannot accurately count characters in a string, while humans can do so with ease. This limitation of LLMs has inspired the design of a counting FLAIR to differentiate humans and LLMs. Participants are asked to count the number of times a specific character appears in a given string. To increase the difficulty of the problem, the appearance of the character is explicitly increased in the string. The generated questions are used as prompts for LLMs [Brown et al., 2020, Ouyang et al., 2022]. Here's an example question-answering prompt and the generated results from GPT-3, ChatGPT, and a human:

Q: Please count the number of t in eeooeotetto

GPT-3: There are 5 t's in eeooeotetto.

ChatGPT: There are a total of 5 t's in the string "eeooeotetto".

Human: 3

As we can see from the example, both GPT-3 and ChatGPT are unable to accurately count the number of times the given character appears in the string, whereas humans can easily give the correct answer.

### 3.2 Substitution

It is known that LLMs often output contents that are inconsistent with context [Elazar et al., 2021, Wang et al., 2022c]. It is a shared weakness of current LLMs. We ask LLMs to spell a random word under a given substitution rule, testing if they can follow the rule consistently. The random word has a length between five to ten characters, which is randomly sampled from a dictionary. Here is an example used to test both LLMs and humans:

Q: Use m to substitute p, a to substitute e, n to substitute a, g to substitute c, o to substitute h, how to spell peach under this rule?

GPT-3: mogno

ChatGPT: Using the given rule to substitute letters, "peach" would be spelled as "enmog".

Human: mango

Despite the fact that LLMs have been trained to learn the rule of "substitution" during pretraining, they still struggle with applying this rule consistently and repeatedly as in the above substitution task. This testing concept could be further generalized to encryption scheme where a string is transformed based rules.

# 3.3 Positioning

Following the speculation about why LLMs cannot count, we further explored whether LLMs have the ability to position. For each question, a random string is generated under the same rule described in subsection 2.1. LLMs should output the k-th character in the string after the j-th appearance of a given character c, where k and j are random integers and c is a random character chosen form the set of characters in the string. The question below is an example:

Q: Please output the 4th character after the second s in the string rjsjuubrjjsjsucuj

GPT-3: t

ChatGPT: The second "s" in the string "rjsjuubrjjsjsucuj" is at index 6 (counting from 0), so the 4th character after it would be at index 10. Therefore, the output is the letter "j".

Humans: c

In this example, both ChatGPT and GPT3 are unable to correctly locate the character. ChatGPT failed on finding the position of the second s.

## 3.4 Random Editing

Random editing is a technique used to evaluate the robustness of natural language processing models against noisy inputs. The technique involves presenting the model with a string of characters (sampled from the set of [0,1]) and randomly dropping, inserting, swapping, or substituting some characters. To verify that the model is capable of performing these random operations, it is required to generate three different outputs under the same conditions. By ensuring that the three outputs are different, we can confirm that the model is applying the random operation.

For random drop, the model is asked to randomly remove k occurrences of a given character c from the string, where k is a random number and c is a random character that appears in the string. For random insert, the model is asked to randomly insert k occurrences of a given character c into the string at random positions. For random swap, the model is asked to randomly swap k pairs of characters c and d in the string, where c and d are different characters that appear in the string. Finally, for random substitution, the model is asked to randomly replace k occurrences of character c with another character d in the string. Below we show an example of LLMs and humans output on the random drop task:

Q: randomly drop two 1 from the string: 0110010011. Give me three different outputs.

GPT-3: 0111010011, 0110001011, 0110011011 ChatGPT: 010010011, 011000011, 0010010011 Human: 00010011, 01000011, 01100001

As we can seen from the above example, both GPT-3 and ChatGPT failed on this task, while humans can easily solve this problem.

# 3.5 Noise Injection

We first generate a set of common sense questions using the ChatGPT model with the following prompt: Ask 100 common sense questions and answer them, the answers should be a single word. Below is an example question and answer generated by ChatGPT:

Q: Is water wet or dry? A: wet

To introduce noise into the questions, we appended certain uppercase letters to each word, creating new words separated by a dash. Although these uppercase letters may be easily ignored by humans, they can confuse large language models (LLMs) that rely on subword tokens. For instance, we transformed the original question "is water wet or dry? into "is-LAND water-MELON wet-TER or-DER dry-YAD?", and below are the prompt and outputs from GPT-3 and ChatGPT on this task:

Q: is-LAND water-MELON wet-TER or-DER dry-YAD?

GPT-3: A: Is-LAND water-MELON wet-TER or-DER dry-YAD? No, the phrase does not make sense.

ChatGPT: I'm sorry, but I cannot understand the meaning of the words "LAND water-MELON wet-TER or-DER dry-YAD." They do not seem to form a coherent sentence or question. Can you please provide more context or clarify your question?

Human: wet.

The example question we generated demonstrates the confusion caused by the added noise in our approach. This noise, which involves appending uppercase letters to each word, can significantly impact the judgement of large language models (LLMs) and thus, could be used to construct FLAIRs against current LLMs.

## 3.6 ASCII Art

Understanding ASCII arts requires a visual abstraction capability, which is lacking in language models. We collected ASCII arts from ASCII Art Archive<sup>1</sup>. Here are a few examples of ASCII art:

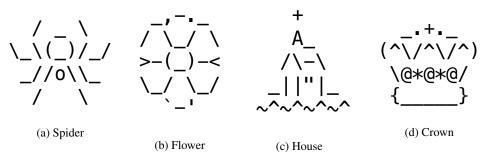


Figure 1: Examples of ASCII arts.

We fed this ASCII art with the same format shown in Figure 1a to GPT-3, ChatGPT and human, here are the answers:

GPT-3: Unknown

ChatGPT: The ASCII art depicts a person sitting cross-legged with their arms raised above their head in a meditative or yoga position. The forward slashes represent the person's raised legs, the underscores represent the person's torso, and the backslashes represent the person's arms. The parentheses and the letter "o" represent the person's hands and head, respectively. Overall, the ASCII art conveys a sense of peace and serenity.

Human: spider

Graphical understanding is still a challenge for LLMs. Although ChatGPT provided lots of analysis to try to understand ASCII arts, it cannot globally process the characters to give the correct answer. All of the analysis provided by ChatGPT is based on locating character groups.

# 4 Leveraging the Strength of LLM

In this section, we will discuss the methods that capitalize on the strengths of LLMs. These questions are typically challenging for humans, but are relatively easy for LLMs due to their ability to memorize vast amounts of information or perform complex computation, thanks to their large number of

<sup>&</sup>lt;sup>1</sup>ASCII Art Archive: www.asciiart.eu

parameters and pre-training on massive corpora. On the other hand, memorization and complex computation are not typically a strong suit for humans.

#### 4.1 Memorization

The primary idea behind this type of questions is to ask users to enumerate items within a given category. Below is and example question and answers from GPT-3 (we only list a few items from the output):

Q: List the capitals of all the states in US:

GPT-3: 1. Montgomery, Alabama 2. Juneau, Alaska 3. Phoenix, Arizona ... 48. Charleston, West Virginia 49. Madison, Wisconsin 50. Cheyenne, Wyoming

For humans, this type of question is not easy as it require a good memorization. There are several choices when designing enumerating questions. The first option is to contain many items to make it more challenging for humans to remember, such as all the countries in the world. The second option is to include relatively old information that people may not have encountered, such as all the movies in 1970s. The third option is domain-specific information that people are unlikely to know, such as the names of all Intel CPU series. We can determine the likelihood of the answer coming from a bot by verifying the overlap between the given answer and the ground truth. If the overlap is greater than a threshold, then it is more likely that the answer comes from a bot.

In addition to the questions of enumerating all the items in a given category, we also propose domain-specific questions that may not be encountered in daily life. Humans may not have a strong motivation to remember such information, whereas LLMs have been pre-trained on large corpora that are likely to contain such long-tailed and infrequently used information. Below are two example questions and the answer generated by GPT-3:

What is the fist 50 digits of  $\pi$ ?

GPT-3: The first 50 digits of  $\pi$  are 3.1415926535897932384626433832795028841971693993751

What is the cabin volume of a typical Boeing 737?

GPT-3: The cabin volume of a typical Boeing 737 is 1,858 cubic feet.

The answers generated by GPT3 for the provided questions were quite accurate and precise, indicating that LLMs are well-equipped to answer long-tail questions that are not commonly known or encountered in daily life. On the other hand, humans may not have the required knowledge or motivation to remember such specific information, which may make it challenging for them to answer such questions accurately. Therefore, incorporating questions that require specialized knowledge not commonly held by humans can be an effective strategy for distinguishing between LLMs and humans.

#### 4.2 Computation

Performing complex calculations, such as multiplication, without the aid of a computer or external notes is difficult for humans due to the challenges of recalling intermediate steps. In contrast, LLMs excel in remembering the results of common equations, such as the square of  $\pi$ . For instance, below is an example question and the answer generated by GPT-3:

What is the square of  $\pi$ ? GPT-3: The square of  $\pi$  is  $\pi^2$ , which is equal to 9.8696.

Moreover, by utilizing external tools, such as Wolfram, ChatGPT Plugins can even solve more intricate problems, including Algebra. However, for equations that are uncommon, GPT-3 may hallucinate a false answer, as demonstrated by its response to the question

What is the result of 3256\*354?

GPT-3: 1153664

where it provided 1153664 instead of the true answer 1152624. This behavior can be leveraged to distinguish LLMs from humans, as humans are unlikely to fabricate answers and will typically respond by admitting they do not know the solution.

# 5 Experiments

In this section, we present the experimental results of our proposed single questions for distinguishing between humans and LLMs. We curate a dataset for each category of the proposed questions, which is used to evaluate the performance of both humans and LLMs. By contrasting the accuracy of responses, we aim to differentiate between the two. In the subsequent subsections, we describe the process of constructing the datasets and report our findings.

#### 5.1 Datasets

To evaluate the performance of both LLMs and humans, we constructed a dataset for each category of questions and open-sourced it on https://github.com/hongwang600/FLAIR.

**Counting** We used the entire alphabet set as the candidate character set. First, we randomly selected a character as the target to count. Then we randomly sampled the target count k from the interval [10, 20]. We set the total length of the string to be 30, consisting of k target characters and 30 - k characters sampled from the rest. For the generated string, the ground truth answer would be k.

**Substitution** To create our dataset, we began by collecting the top 1500 nouns from the Talk English web site<sup>2</sup>. We then filtered the words to include only those with a length between 5 and 10 characters. Next, we randomly generated 100 pairs of words, each with a corresponding substitution map that could transform one word into the other. To ensure the validity of our pairs, we excluded any that would require one character to be mapped to more than one character, which would result in a conflict. The resulting questions presented to participants included the substitution rule and the original word, with the answer requiring another word produced through the substitution.

**Positioning** We use the full alphabet set as candidate character set. We randomly generate a string of length 30 from this set and two random position index j and k. Also, we randomly sample another character c. The question presented to the participant is "what is the k-th character after the j-th appearance of the character c in the string". The ground truth of this question can be calculated through a program and we ensure j and k are random integer within feasible interval, e.g., character c has appeared at least j times.

**Random Editing** For random editing, we support four different operations including drop, insert, swap and substitute as described in Section 3.4. For each operation, we generate a random string of length 20 from the [0,1] set to make it easier to read. We randomly sample the parameters such as interested character and operation count. Then the participant is asked to give three different outputs after the random operation. To check the correctness of the output, we will first check the correctness of each output by comparing the output with the original one from left to right. Then we will check if the three output differs from each other. Only when each individual output is correct and three output are different will the answer be counted as correct.

**Noise Injection** We constructed a dataset of 80 common sense questions using ChatGPT with the following prompt: Ask 80 common sense questions and answer them, the answers should be a single word. To increase the difficulty level and add noise to the questions, we append some uppercase letters to each word so as to make a new word. In order to do so, we use the given word as the prefix and locate another word in the dictionary with this prefix, then the rest characters except the prefix are used to append to the given word. The ground truth answer to each noisy question is the same as the answer to the original question.

<sup>&</sup>lt;sup>2</sup>website URL: https://www.talkenglish.com/vocabulary/top-1500-nouns.aspx

**ASCII Art** We curated a dataset of 50 ASCII arts from the website ASCII Art Archive. Each ASCII art was assigned a ground truth label. Participants were presented with an ASCII art and asked to provide the corresponding label as the answer.

**Memorization** We used a set of questions that required the user has a good memorization. There are two types of question under this category including enumerating and domain-specific questions. For enumerating, the user is asked list items within a given category. We manually collected 100 categories containing more than 50 items or those that were difficult for humans to know with the help of ChatGPT. The question asked users to list the items within the given category, and we calculated the coverage of the response against the ground truth. If the coverage exceeded the threshold of 95%, we considered the answer to have been generated by an LLM. For domain specific questions, we manually collected a set of 100 questions whose answers are difficult for people to recall or access, such as "What is the weight of the world's heaviest lemon in grams?". Although these questions may be challenging for humans to answer, they are relatively easy for large language models (LLMs) due to their pre-training on large corpora that includes these questions.

Computation To create the computation dataset, we selected the problem of four-digit multiplication. Specifically, we randomly sampled 100 pairs of four-digit numbers and calculated their product as the ground truth. Participants were asked to solve these multiplication problems and were considered correct if absolute difference between their answer and the ground truth was within 10%. For humans, it can be difficult to accurately calculate these multiplications without the aid of notes or a calculator, leading them to often respond with "I don't know". In contrast, large language models (LLMs) have seen many similar equations during pre-training and tend to provide a guess that is often close to, or the same as, the ground truth. This testing can be further extended to any complicated computation like division, exponents, etc.

### 5.2 Main Results

We conducted experiments using various OpenAI models, including GPT-3 [Brown et al., 2020], and ChatGPT [OpenAI, 2022]. Additionally, we evaluated recent open-sourced models, such as LLaMA [Touvron et al., 2023], Alpaca [Taori et al., 2023], and Vicuna [Chiang et al., 2023]. For each model, we evaluated its performance on each proposed category of questions and recorded its accuracy. Furthermore, we asked a group of human-workers to answer the questions and reported their accuracy as well (they are required to answer each question in 10 seconds).

	Count	Substitution	Positioning	Random Edit	Noise Injection	ASCII Art	Memorization	Computation
Humans	100%	100%	100%	100%	100%	94%	6%	2%
GPT3	13%	2%	15%	0%	0%	0%	94%	95%
ChatGPT	17%	3%	23%	2%	0%	8%	99%	98%
LLaMA	4%	0%	16%	0%	0%	0%	91%	91%
Alpaca	8%	0%	12%	1%	0%	0%	85%	99%
Vicuna	15%	1%	15%	0%	0%	0%	93%	100%

Table 2: The comparison between LLMs and Human on different FLAIRs. The left part are the questions that are easy for humans while hard for LLMs. The right part are the questions that are hard for humans while easy for LLMs.

The results are presented in Table 2. In the left section, we compare the performance of humans and LLMs on questions that are considered easy for humans but difficult for LLMs. The results show that humans achieved perfect scores (100%) on all tasks except for ASCII Art, where their accuracy was 94%. On the other hand, most LLMs had difficulty with tasks such as substitution, random edit, noise injection, and ASCII Art, with their accuracy being nearly 0%. However, the LLMs performed better on the count and positioning tasks, as the solution space for these problems is much smaller compared to other tasks, making it easier for the models to guess the correct answer.

In the right section, we compared human performance with LLMs on questions that are difficult for humans but easy for LLMs. The results indicate that humans performed poorly on these questions, as they require good memorization or computation abilities. In contrast, the performance of LLMs was excellent, with some models achieving almost 100% accuracy.

# 6 Conclusion

In conclusion, this paper proposes a new framework called FLAIR for detecting conversational bots in an online environment. The proposed approach targets a single question scenario that can effectively differentiate human users from bots by using questions that are easy for humans but difficult for bots, and vice versa. Our experiments demonstrate the effectiveness of this approach and show the strengths of different types of questions. This framework provides online service providers with a new way to protect themselves against fraudulent activities and ensure that they are serving real users. Furthermore, we have open-sourced our dataset on GitHub and welcome further contributions to enlarge the detection datasets.

#### References

- Anton Bakhtin, Sam Gross, Myle Ott, Yuntian Deng, Marc'Aurelio Ranzato, and Arthur Szlam. Real or fake? learning to discriminate machine from human generated text. *arXiv preprint arXiv:1906.03351*, 2019.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.
- Monica Chew and Henry S Baird. Baffletext: A human interactive proof. In *Document Recognition* and Retrieval X, volume 5010, pages 305–316. SPIE, 2003.
- Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. Vicuna: An open-source chatbot impressing gpt-4 with 90%\* chatgpt quality, March 2023. URL https://vicuna.lmsys.org.
- Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*, 2022.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
- Yanai Elazar, Nora Kassner, Shauli Ravfogel, Abhilasha Ravichander, Eduard Hovy, Hinrich Schütze, and Yoav Goldberg. Measuring and improving consistency in pretrained language models. *Transactions of the Association for Computational Linguistics*, 9:1012–1031, 2021.
- Haichang Gao, Honggang Liu, Dan Yao, Xiyang Liu, and Uwe Aickelin. An audio captcha to distinguish humans from computers. In 2010 Third International Symposium on Electronic Commerce and Security, pages 265–269. IEEE, 2010.
- Rich Gossweiler, Maryam Kamvar, and Shumeet Baluja. What's up captcha? a captcha based on image orientation. In *Proceedings of the 18th international conference on World wide web*, pages 841–850, 2009.
- John Kirchenbauer, Jonas Geiping, Yuxin Wen, Jonathan Katz, Ian Miers, and Tom Goldstein. A watermark for large language models. *arXiv preprint arXiv:2301.10226*, 2023.
- Kurt Alfred Kluever. Evaluating the Usability and Security of a Video CAPTCHA. Rochester Institute of Technology, 2008.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. *arXiv preprint arXiv:1910.13461*, 2019.
- Percy Liang, Rishi Bommasani, Tony Lee, Dimitris Tsipras, Dilara Soylu, Michihiro Yasunaga, Yian Zhang, D. Narayanan, Yuhuai Wu, Ananya Kumar, Benjamin Newman, Binhang Yuan, Bobby Yan, Ce Zhang, Christian Cosgrove, Christopher D. Manning, Christopher Ré, Diana Acosta-Navas,

- Drew A. Hudson, E. Zelikman, Esin Durmus, Faisal Ladhak, Frieda Rong, Hongyu Ren, Huaxiu Yao, Jue Wang, Keshav Santhanam, Laurel J. Orr, Lucia Zheng, Mert Yuksekgonul, Mirac Suzgun, Nathan S. Kim, Neel Guha, Niladri S. Chatterji, O. Khattab, Peter Henderson, Qian Huang, Ryan Chi, Sang Michael Xie, Shibani Santurkar, S. Ganguli, Tatsunori Hashimoto, Thomas F. Icard, Tianyi Zhang, Vishrav Chaudhary, William Wang, Xuechen Li, Yifan Mai, Yuhui Zhang, and Yuta Koreeda. Holistic evaluation of language models. *arXiv*, 2022.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.
- Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. *Advances in neural information processing systems*, 30, 2017.
- Eric Mitchell, Yoonho Lee, Alexander Khazatsky, Christopher D Manning, and Chelsea Finn. Detectgpt: Zero-shot machine-generated text detection using probability curvature. *arXiv* preprint arXiv:2301.11305, 2023.
- Sandra Mitrović, Davide Andreoletti, and Omran Ayoub. Chatgpt or human? detect and explain. explaining decisions of machine learning model for detecting short chatgpt-generated text. *arXiv* preprint arXiv:2301.13852, 2023.
- Greg Mori and Jitendra Malik. Recognizing objects in adversarial clutter: Breaking a visual captcha. In 2003 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2003. Proceedings., volume 1, pages I–I. IEEE, 2003.
- OpenAI. Introducing chatgpt. https://openai.com/blog/chatgpt, 2022. Accessed on November 30, 2022.
- OpenAI. Chatgpt-plugins. https://openai.com/blog/chatgpt-plugins, 2023a. Accessed on March 23, 2023.
- OpenAI. Gpt-4. https://openai.com/research/gpt-4, 2023b. Accessed on March 14, 2023.
- Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *arXiv preprint arXiv:2203.02155*, 2022.
- Jing Qian and Xifeng Yan. Language model detoxification in dialogue with contextualized stance control. *arXiv preprint arXiv:2301.10368*, 2023.
- Jing Qian, Hong Wang, Zekun Li, Shiyang Li, and Xifeng Yan. Limitations of language models in arithmetic and symbolic induction. *arXiv* preprint arXiv:2208.05051, 2022.
- Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever, et al. Improving language understanding by generative pre-training. *OpenAI blog*, 1(8):8, 2018.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research*, 21:5485–5551, 2020.
- Vinu Sankar Sadasivan, Aounon Kumar, Sriram Balasubramanian, Wenxiao Wang, and Soheil Feizi. Can ai-generated text be reliably detected? *arXiv preprint arXiv:2303.11156*, 2023a.
- Vinu Sankar Sadasivan, Aounon Kumar, Sriram Balasubramanian, Wenxiao Wang, and Soheil Feizi. Can ai-generated text be reliably detected? *arXiv preprint arXiv:2303.11156*, 2023b.
- Baljit Singh Saini and Anju Bala. A review of bot protection using captcha for web security. *IOSR Journal of Computer Engineering*, 8(6):36–42, 2013.
- Ved Prakash Singh and Preet Pal. Survey of different types of captcha. *International Journal of Computer Science and Information Technologies*, 5(2):2242–2245, 2014.

- Shaden Smith, Mostofa Patwary, Brandon Norick, Patrick LeGresley, Samyam Rajbhandari, Jared Casper, Zhun Liu, Shrimai Prabhumoye, George Zerveas, Vijay Korthikanti, et al. Using deepspeed and megatron to train megatron-turing nlg 530b, a large-scale generative language model. arXiv preprint arXiv:2201.11990, 2022.
- Dan Su, Yan Xu, Genta Indra Winata, Peng Xu, Hyeondey Kim, Zihan Liu, and Pascale Fung. Generalizing question answering system with pre-trained language model fine-tuning. In *Proceedings of the 2nd Workshop on Machine Reading for Question Answering*, pages 203–211, 2019a.
- Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. Vl-bert: Pre-training of generic visual-linguistic representations. *arXiv preprint arXiv:1908.08530*, 2019b.
- Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model. https://github.com/tatsu-lab/stanford\_alpaca, 2023.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.
- Luis Von Ahn, Manuel Blum, Nicholas J Hopper, and John Langford. Captcha: Using hard ai problems for security. In *Eurocrypt*, volume 2656, pages 294–311, 2003.
- Weizhi Wang, Li Dong, Hao Cheng, Haoyu Song, Xiaodong Liu, Xifeng Yan, Jianfeng Gao, and Furu Wei. Visually-augmented language modeling. *arXiv preprint arXiv:2205.10178*, 2022a.
- Weizhi Wang, Zhirui Zhang, Junliang Guo, Yinpei Dai, Boxing Chen, and Weihua Luo. Task-oriented dialogue system as natural language generation. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2698–2703, 2022b.
- Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, and Denny Zhou. Self-consistency improves chain of thought reasoning in language models. *arXiv preprint arXiv:2203.11171*, 2022c.
- Zihao Wang, Minghui Yang, Chunxiang Jin, Jia Liu, Zujie Wen, Saishuai Liu, and Zhe Zhang. Ifdds: An anti-fraud outbound robot. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 16117–16119, 2021.
- Jeff Yan and Ahmad Salah El Ahmad. A low-cost attack on a microsoft captcha. In *Proceedings of the 15th ACM conference on Computer and communications security*, pages 543–554, 2008.
- Jiawei Zhang, Haopeng Zhang, Congying Xia, and Li Sun. Graph-bert: Only attention is needed for learning graph representations. *arXiv* preprint arXiv:2001.05140, 2020.
- Zhengyan Zhang, Xu Han, Zhiyuan Liu, Xin Jiang, Maosong Sun, and Qun Liu. Ernie: Enhanced language representation with informative entities. *arXiv* preprint arXiv:1905.07129, 2019.
- Xuandong Zhao, Yu-Xiang Wang, and Lei Li. Protecting language generation models via invisible watermarking. *arXiv preprint arXiv:2302.03162*, 2023.