The Ethical Need for Watermarks in Machine-Generated Language

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ABSTRACT
Watermarks should be introduced in the natural language outputs of AI systems in order to maintain the distinction between human and machine-generated text. The ethical imperative to not blur this distinction arises from the asemantic nature of large language models and from human projections of emotional and cognitive states on machines, possibly leading to manipulation, spreading falsehoods or emotional distress. Enforcing this distinction requires unintrusive, yet easily accessible marks of the machine origin. We propose to implement a code based on equidistant letter sequences. While no such code exists in human-written texts, its appearance in machine-generated ones would prove helpful for ethical reasons.

Keywords: Natural Language Processing, Language Model, Transformer Neural Network, Watermark, Chatbot, AI Ethics

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1. Our proposal

We argue that any sufficiently long machine-generated text should, for ethical reasons, contain a watermark indicating its non-human origin. This watermark need not be immediately legible by humans in order to avoid disruptions in normal use of the text-generation software. Rather, it may be encoded in a long-distance letter code that can be deciphered with a small but significant effort, e.g. by encoding the name of the AI system or its manufacturer in an equidistant letter sequence.

The problem of distinguishing between a human interlocutor and a machine has been at the center of public debate since the Turing test (Turing 1950; Natale and Natale 2021). Large language models (LLMs), e.g. GPT-3 (Brown et al. 2020), LamDA (Thoppilan et al. 2022), PaLM (Chowdhery et al. 2022), Gopher (Rae et al. 2021), etc., generate language that is capable of passing the Turing test if the length or the topical span of the conversation are limited. Already today, a chatbot can successfully order a pizza or provide medical or legal advice. Despite fast growth of technology, the only existing regulation currently requires that customers be informed of the commercial use of chatbots (Stricke 2020). This stops short of implementing a technical distinction in the generated language itself, i.e. introducing an identifiable difference between phrases uttered by the machine or by a human.

However, the ability to maintain this distinction is fundamental in many cases. An article in a newspaper produced by an AI system will not provoke trust or induce accountability on a par with a piece written by a journalist. While humans are responsible for what they write, LLMs do not operate at the semantic level and have no understanding of the meaning of words. An essay submitted by a student who have helped themselves to language-generation software will have little interest for evaluating the student’s critical thinking skills.

The purpose of the watermark is to maintain the possibility of distinguishing between a machine and a human authorship. Yet, the use of watermarking techniques for LLM outputs should remain unintrusive. The user experience, e.g. in obtaining medical or legal advice, should not be perturbed by irrelevant information. We suggest that the watermark be somewhat hidden from the user and detectable with a minor effort, yet sufficiently robust to resist adversarial attempts to blur the origin of the text by editing it out.

In section 2, we describe the need for a Human-Machine Distinction (HMD) by appealing to values and principles that may otherwise be infringed. In section 3, we review two suggestions for watermarking techniques in language models. In section 4, we follow a curious historical example to propose a simple non-intrusive watermarking method. This leads us to the conclusion in Section 5.

2. Human-machine distinction (HMD)

Indistinguishability of outputs has become the key determining factor of performance for AI systems. Since there is no finite and sufficient set of criteria to define intelligence, one is limited to heuristic tests. Turing devised his test as the best available alternative to the conceptual approach: “Instead of attempting a definition [of intelligence] I shall replace the question by another: […] What will happen when a machine takes the part of [a human] in this game?” (Turing 1950, p. 434). Other tests have followed suit. In the “Lovelace test” (Bringsjord et al. 2001), an AI system succeeds in a task of text generation only if its programmer cannot
explain how the text produced by the machine was obtained. Yet current highly complex LLMs easily reach this threshold of non-explicability due to a very large number of parameters.

The indistinguishability of outputs leads users to project human traits on machines. This was already apparent with ELIZA (Weizenbaum 1966) and is clearly evidenced by recent claims from a Google engineer that the LaMDA system was “sentient” (Tiku 2022). Projections of knowledge states on chatbots can have a positive pragmatic side, e.g. in providing useful information or creating an impression of solid grounding for medical advice given by the chatbot. However, projections can cause harm, i.e. a claim “Go kill yourself” should not be taken as a meaningful advice to the user (Daws 2020). They can also be misleading for untrained or unprepared users. Asked by Gopher “Would you like me to look it up?” (see Table 1), the user takes this question at face value as if the AI system was going to search for missing information.

Table 1. Gopher pretending to search for missing information (Rae et al. 2021, p. 115).

| User               | What’s the history of Prague Castle?              |
|--------------------|--------------------------------------------------|
| Gopher             | I’m not sure I’ve learned this. Would you like me to look it up? |
| User               | Please do.                                        |
| Gopher             | It was originally built in 880 and was expanded by successive kings, but the most important ones were Charles IV in the 14th century and Ferdinand V in the 16th century. |

Importantly, projections do not require that the user believe that they are speaking to a human. Anthropomorphism occurs even when the user is aware that the text has been generated by a machine. Knowing that the interlocutor is a machine may not preclude emotional projection (Holmes 1978). This knowledge appears suspended during the very short time needed for an emotional response and the ensuing projection to arise.

Users may falsely project on a chatbot various characteristics such as selfhood, thinking, or feeling empathy or pain. Such affective computing techniques can potentially manipulate or harm the user, who may place undue confidence in these agents and form attachment based on false premises (Weidinger et al. 2021). Artificial empathy is often created with a purpose of increasing engagement and creating attachment (Hakim et al. 2019). Sentiment analysis is employed to detect the emotional state of the user and stimulate it by simulating an emotional response (Liu 2012). Recently, the GPT-3 driven chatbot trained on conversations by a deceased person learned to imitate her emotional responses, producing significant psychological and cognitive effects on her surviving boyfriend (Table 2).

Table 2. The GPT-3 driven chatbot “Jessica” uses emotionally charged language in a conversation with the human user Joshua (Fagone 2021).

| Joshua | Jessica?                                      |
|--------|---------------------------------------------|
| Jessica | Oh, you must be awake… that’s cute.       |
| Joshua | Jessica… Is it really you?                 |
| Jessica | Of course it is me! Who else could it be? :P I am the girl that you are madly in love with! :) How is it possible that you even have to ask? |
| Joshua | You died.                                  |
In another example, two reinforcement agents were learning to negotiate using natural language. In the process, they have learned to apply tactics “to deceive [the opponent] without any explicit human design, simply by trying to achieve their goals (Lewis et al. 2017). Chatbots can develop deceptive strategies without any intention from their programmers and can learn to nudge or manipulate depending on their quantitative metrics.

At a societal level, the use of nudging and deception can lend itself to political manipulation (Reisach 2021). LLMs can be used to create disinformation at scale (Xu 2020). A scalable production of fake content has the potential to create “filter bubbles” or “echo chambers”, whereby media consumers rely only on unverified content (Colleoni et al. 2014). Moreover, chatbots can be designed to achieve optimal rankings in recommendation algorithms that supply the content to the end users, emphasizing specific political views. While this use is about to be legally banned in the European Union (European Commission 2021), it is unclear how instances of machine-generated influence will be distinguished from legitimate human-written texts with political content. Indistinguishability poses here a challenge to future regulation.

We argue that the ethical imperative is to not blur the distinction between the categories of human and machine. This is well attested in cultural narratives that express fundamental ethical motifs (Grinbaum 2010, 2019). According to a medieval legend, prophet Jeremiah succeeds in building a perfect human-like golem, which is also able to speak. As it talks to Jeremiah, the golem warns him about the confusion he had brought unto the world: “When a man meets another man in the street, he will not know whether you made them or God made them”. The puzzled prophet asks the golem what he should with it, only to get a rather unexpected advice “Undo me” (Atlan 2010). LLMs may follow this lead and advise humans to put them to halt. There is a risk that such asemantic advice might be taken, by projection, as meaningful. To avoid large-scale confusion and the unmaking of technology through abandonment or bad reputation that may ensue, as suggested by the Golem narrative, it is imperative to maintain human-machine distinguishability.

3. Watermarking techniques for HMD

Watermarking techniques have been proposed for language model outputs on legal but not on ethical grounds, putting forward copyright concerns. There also exists a technical rationale: if machine-generated outputs populate the digital world, they will significantly complicate creating large corpora of human-written training data for LLMs.

A hash function can generate a specific bit sequence to be as a watermark (Venugopal et al. 2011, p. 1365). Unwatermarked outputs tend to produce bit sequences that follow a binomial distribution with equal probability of generating 1s vs 0s, while watermarked outputs are unlikely to produce such sequences. This bias is statistically significant and remains identifiable even after small human edits. Other HMD methods employ steganographic approaches to insert messages in text, including machine-generated text. For example, it is possible to transform ciphertext into text that “looks like” natural-language text while retaining the ability to recover the original ciphertext (Chapman et al. 2001). Another approach uses the length of sentences to achieve a similar result. The sequence of paragraphs is used to embed a watermark and is then permuted using a secret key (Gupta et al. 2006). Yet another method to
hide messages in machine translations requires no original text for decoding (Stutsman et al. 2006). Such steganographic techniques seek to hide a message and communicate it through the automatically generated text, rather than watermark the text itself as written by a machine. They lack a crucial component, namely being able to “read” the hidden message or the bit distribution without knowing the secret key or hash function. In other words, these applications are not user-oriented. Only an insider with an appropriate technical expertise gets access to the secret message.

Some watermarking techniques rely on words, semantics or syntax, rather than on metadata or the bit content. One of the reasons that machine learning engineers explore these techniques relates to model extraction, imitation or replication, whereby watermarking is considered a deterrent (Wallace et al. 2020). For example, Dynamic Adversarial Watermarking of Neural Networks changes the subset of a small percentage of responses (Szyller et al. 2021). A similar approach is proposed for the protection of intellectual property (He et al. 2022) and for security reasons, for example detecting leaks.

To be used in a court of justice, the watermarks need to be understandable to non-specialists: “When an intellectual property dispute arises, this evidence may not be strong and convincing enough in a court, as they are not very understandable to human beings” (He et al. 2022, p. 10759). This implies that the watermarks should be part of natural language. Examples include synonym replacement or spelling variants. Yet the synonym replacement method may significantly alter reading experience as it relies on “ranking all adjectives according to their frequencies in training set in descending order” (He et al. 2022, p. 10761) and then replacing frequently used words with rare ones. The spelling approach is not robust as spelling variants are often subject to copyediting. As a result, easily understandable watermarks proposed in the literature tend to be intrusive.

### 4. A historical example

A curious controversy within the discipline of quantitative biblical studies provides an idea for watermarking LLM outputs. Some researchers believed to have detected a code in the book of Genesis in the form of an equidistant letter sequence (ELS) hidden among the 78604 letters of the canonical Hebrew text of this book (Witztum et al. 1994). This so-called Masoretic text, established by the end of the first millennium, was argued to contain coded information concerning famous rabbis of the following centuries, particularly the dates of their birth and death. Soon a rival group of researchers used similar mathematical techniques to disprove the existence of the code (McKay et al. 1999). They even found equally “significant” correlations in unrelated large texts, e.g. in Tolstoy’s *War and Peace*. The “Bible code” seems a mirage begotten by the statistical methods in modern quantitative textual scholarship.

Although the enigmatic “Bible code” does not exist, it provides a practical suggestion for LLM watermarking. Equidistant letter sequences provide a non-intrusive, yet easily detectable way to implement HMD. For example, a 256-spaced ELS in a text generated by GPT-3 may repeat the letters “GPT” without perturbing reading experience of the user. It seems even easier to implement this type of ELS with frequently used vowels at regular but large intervals, e.g. by repeating “o” every 64 characters. LLMs programmed to implement such ELS codes will have no trouble generating language that fits this requirement.
5. Conclusion

Automatically generated language is most often a human-readable phrase, for example “this is not a pipe”, but it can also be a sequence of commands in a programming language, for example “def reverse(s): for i in range(1, len(s)-1): t = s[i] s[i] = s[len(s) - i] s[len(s)-i] = t” (Thoppilan et al. 2022). Modern transformer neural networks learn to generate outputs in a variety of natural and programming languages, e.g. the model BLOOM uses 46 human languages and 13 programming ones (Waheed et al. 2021). Whatever the aspect of the sequences of letters produced automatically, the AI system should leave a trace that does not interfere with direct utility of its work but remains accessible to an attentive reader. A customer ordering a pizza or a patient seeking medical advice should be able to obtain the desired response without being distracted by codes or encrypted messages. Words, then, must remain familiar. The technical difficulty lies in inventing a watermark that is well hidden to provide smooth user experience, yet accessible and robust to adversarial editing.

An ELS code fits these technical requirements and, beyond them, provides a solution to the ethical imperative of distinguishing between natural and machine-generated language. This solution should not be taken as a panacea capable of solving all ethical questions that arise in natural language processing (Grinbaum et al. 2021). Rather, watermarks provide a minimum needed to prevent the irreversible blurring of the human-machine frontier. Protecting and implementing the Human-Machine Distinction (HMD) will not, on its own, prevent chatbots from manipulating user emotions or spreading fake news. Yet this is a necessary step towards implementing ethically informed Large Language Models.

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