

Machine Translation vs. Human Translation: Quality, Challenges, and Perceptions

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Abstract: Language translation has been transformed due to the rapid advancement of machine translation (MT) technologies, which provide scalable, low cost and fast solution for linguistic barrier. While machine translation capabilities in translating into multiple languages and across different disciplines is improving through artificial intelligence, neural networks and natural language processing. The degree of equivalence in terms of relevance, quality and reliability between MT and HT remain a point of debate despite developments in dynamic translation tools. Machines don't have the cultural sensitivity, fine-tuned context awareness and understanding of idiomatic nuance as humans. It analyzes machine translation against human translation in terms of three perspectives, namely quality, problems and users. First by the comparison of its outputs with high-quality human translations, proficient in the source language and culture (commonly referred to as human translation) on correctness, fluency, and adequacy. However, if MT is good for analyzing large volumes of text and standard phraseology, it often fails to cope with context dependent expressions, ambiguity (especially polysemy), especially when dealing with literature, law and technology. Secondly, it emphasizes the limitations of existing machine translation (MT) (e.g., lack of understanding context, challenges with low-resource languages, use of domain terminology and ethical issues such as data privacy or loss of jobs for human translators). Translation by a human translator is more accurate, culturally sensitive and stylistically versatile, but slower and more expensive. Third, this article examines the attitudes of translators, end users and organizations toward MT and HT. It proves that although MT's speed and cost are agreeable, concerns about accuracy, reliability and idiomatic errors are still fudging the picture. The piece also delves into the hybrid approaches that pair machine learning with human expertise, looking at collaborative workflows and post-editing to enhance quality without sacrificing efficiency. The report acknowledges the benefits of both machine and human translation as part of a hybrid model consistently helping organizations to weigh up quality, cost and time. To the aim of this contribution lies in offering a comprehensive understanding of how translation practice has been evolving during the digital age by focusing on recent scholarship, empirical research and industry approaches. The findings indicate that MT is insufficient by itself and should not pose a threat to the context-dependent judgments, cultural and interpretative knowledge of human translators. In addition to offering support for language translation in a technologically enhanced, globalized world, for practitioners, teachers and organizations, the study contributes to ongoing debates on the interrelationship of MT and HT.

Keywords: Neural Machine Translation Post-Editing, User Perception of Machine Translation and Human Translation, Quality In Translation, Difficulties in Translation, Cultural Sensitivity Intranslating, Hybrid T Ranslation Linguisticaccuracy.

I. INTRODUCTION

Language is the most powerful basic tool of culture, communication and knowledge exchange. In today's globalized world, the need for accurate and efficient translation is on the rise, and therefore solutions are needed to bridge language barriers in different settings. If we have learned anything from the origins of MT, it is that human translation (HT) has always been considered the gold standard for delivering accurate and culturally sensitive translations. Humans "The translation and interpretation of meaning is a highly complex process that relies on an immense background knowledge of language, culture and interaction. These abilities are of particular value in professions which require precision and cultural nuance such as legal, medical, literary, technical translation. With the penetration of digital technology, computer-assisted translation including machine translation (MT) has emerged as a popular alternative which offers fast, cost-effective and scalable means of translating languages. Most first-generation machine translation (MT) systems were rule-based and, as such, not well adapted for idiomatic expressions, complex syntactic structures or the many shades of meaning provided by context. Yet due to advances in artificial intelligence and the development of neural network-based translation systems, such as Google Translate and DeepL's AI-powered translation tools, Neural Machine Translation (NMT) has come into existence. These systems leverage large data sets and sophisticated algorithms to produce more accurate, fluent, domain-specific



translations. The growth in popularity of MT, both in private life as well as the professional and educational environment, highlights a potential success that threatens to revolutionise the translation industry.

Despite these advances, MT has limitations. The MT systems do not have the cultural, context or colloquial idioms experience as human translators. Specialist jargon, ambiguities and polysemous words normally lead to mistranslations that damage the text accessibility and comprehension. Literary texts containing metaphorical or idiomatic expressions are rather difficult for MT, often producing translations which are faithful in meaning but unnatural in style. Moreover, MT systems provide a varying level of performance across languages, often performing poorly for low-resource languages due to the insufficient amount of training data. The many challenges of MT raise vexing questions about the quality, reliability and usability of MT, particularly when accuracy in translation is paramount. Human translation, however, is still superior although slower and more expensive but not so much in domain or culturally specific contexts. A human translator is able to convey tone and style, navigate socio-cultural quirks, subtle idioms that robots just can't parse. They have the flexibility, wisdom and interpretational judgement to give a nuanced translation that will silence various demanders at different paces. However, due to the high cost, time (and effort) intensive nature of HT, there is an on-going effort by academia and industry to explore hybrid models where both MT and MTPE are combined. These models aim to address the pressures of contemporary translation by combining the efficiency of machine translation (MT) with the confidence of human knowledge.

User acceptance and opinion is also an important factor in translation. Extending these contributions to include a sed interface such as at is beneficial for the end users and organizations, who often praise being able to achieve MT on there terms so long as the output does not equal garbage. 2 Organizations that consider MT love it for its fast, cheap goods but are suspicious of its reliability, especially in high-risk domains like legal or medical translation. By contrast, instead of regarding MT systems as a replacement, human translators are beginning to exploit these to stay more productive. This changing landscape implies a co-working mode in which consideration of human expertise provides for correctness, cultural connotation, and stylistic closeness while the MT being used to helpus themake drafts. Following a deep review of the literature, both academia and industry practices as well as technical advances are analyzed in terms of quality, hurdles and perceptions of MT vs. HT. The research underlines the strengths and weaknesses of machine and human translation as complementary processes in Contemporary Language Practice. By bringing to the fore the promise of collaborative, hybrid models to optimize translation outputs in a world that is increasingly globalized and digitally mediated, this project hopes above all to inform translators as well as organizations and policy makers on pragmatic/ethical operational considerations in regard to MT and HT.

II. COMPARATIVE QUALITY OF MACHINE AND HUMAN TRANSLATION

A. Accuracy and Fidelity

Human translators are very effective when it comes to translating text understandably and with context, especially difficult materials such as marketing content, legal documents or literature. They understand cultural references, idioms, and nuances that MT systems often mangle. ACL Anthology, for instance, demonstrated the consistent preference of human translations over MT outputs in terms of quality assessment on German translations from the same English source text while MT tends to have fluency and coherence issues. On the contrary, in spite of recent improvements, MT technologies struggle with syntactic complexity as well as polysemy and ambiguity. Student strengths MT systems have problems with negation; one of the simplest features of language, and add significantly to a large number of translation errors.

B. Speed and Cost

Because of its unmatched speed and low cost, MT is great for instances where you need to get a lot of translation done fast. Machine Translation Post-Editing (MTPE) refers to a human-translator post-editing process aiming at the quality enhancement of MT outputs. It has been found that MTPE quality can be comparable to HT, but the efficiency gains will as always rely on the quality of the raw MT and post-editor PLOS skills.

III. CHALLENGES IN MACHINE TRANSLATION

A. Contextual Understanding

Among the natural language processing (NLP) paradoxes that machine translation (MT) cannot adequately cope with is the fact that machine translations (MTs) can hardly capture contextual meaning. Human language, with tone, style, cultural references, implied meaning and syntax and vocabulary is naturally ambiguous and dependent on context. In translating the text using human translators, such revelatory information could be detected and factored into translation so that the intended meaning and pragmatics are preserved as in source. On the other hand, MT systems-including the state-of-the-art deep learning-based neural machine translation (NMT) models-heavily rely on statistical patterns and associations that are acquired from large corpora. While such systems can produce grammatically and idiomatically correct output, they often fail to capture finer shades of context that inform the meaning of an expression resulting in translations which could be morphologically but not semantically valid. A professional translator has the ability to recognize figurative usage across

idiomatic expressions, culturally specific metaphors – “spill the beans,” “walking on eggshells” – and translate them realistically in such a way that meaning is maintained as well as tone. But many times, MT systems may translate such terms as is, causing the output to be ambiguous, inconsistent or culturally inappropriate. Also polysemy – words containing more than one meaning, has to be understood in context. The words 'charge' may mean an electric phenomenon, a military onslaught or even a monetary expense. MT systems can opt for the wrong translation without context, leading to semantic errors that significantly alter meaning.

In technical (legal, medical) areas where exact phrasing and specific terminology really matter, context is also important. Let us consider domain-specific semantics before detecting imprecise or misleading translations generated by MT systems that are trained over general corpora. Other challenges are coherence and organization of texts at discourse level. Humans can read a paragraph or document holistically, and determine that it makes sense, is internally consistent and has resolved its references (e.g., pronouns; anaphora). Existing MT systems often translate only isolated sentences, without considering the relationship between sentences and consequently producing incomprehensible or broken text. Recent works have approached to the limitation of context by introducing novel techniques such as transformer structured models, attention mechanisms or document-level NMT. These techniques aim at incorporating local context and larger spans into the predictions. While they are promising, they still do not match human-level performance in understanding the intended tone along with cultural differences and pragmatic aspects. This means that human supervision is still required for these and other sensitive applications, such as marketing, diplomatic relations and literary translation. It is often the case that even professionally produced translations need to be post-edited when obtained using an MT system (to ensure fitness for purpose, enjoyability and text domain fidelity).

Conclusion Though MT has come a long way in the past years, one large challenge remains in the lack of profound contextual understanding. When it comes to interpreting complex language, delicate connotations and culturally specific material, human translators still hold the upper hand. The only way to close this gap and achieve high-quality, context-sensitive translation is through hybrid workflows that combine the efficiency of machine translation with human interpretive skills.

B. Linguistic Diversity

There exists a fundamental linguistic variation issue for the machine translation systems. Machine translation (MT) has made incredible advances in high resource languages like English, Spanish, French and Mandarin, yet it remains a tremendous struggle for low resource ones which lack sufficient digital data to train models effectively. Low-resource languages are those which have limited or no parallel corpora, lexicons, or annotated datasets (e.g., native, minority, or less frequently written). The quality of translation suffers due to this data shortage which results in often misleading, grammatically incorrect or contextually irrelevant translations. For example, in cross-lingual transfer pairs with lower resources, such as Welsh-Urdu or Hausa-Japanese, the machine translation model trained mostly on English-Spanish or English-Chinese corpora does not work so well. The lack of a training corpus is an obstacle to the system's ability to pick up correct syntax, semantics and colloquial idioms. Also, many low-resource languages have linguistic properties such as complex morphology systems, agglutinativity or non-linear word order that are less frequent in high-resourcelanguages. Such fine-grained structural nuances are not captured by MT models, which can lead to translated outputs where meaning or grammatical relations are misconstrued.

Apart from low resources languages, dialectal variation and regionalisms in language or language change are problematic for MT pipelines. Arabic, for instance, includes several dialects which have their phonetic features, syntax and lexicon in addition to Modern Standard Arabic (MSA). MSA-trained MT systems often have problems with dealing with dialectal variation, which limits their applicability in everyday use. Data-informed machine translation models also face additional challenges, since many indigenous and minority languages are oral-based with limited or no standardized written form. Cultural and field-specific translation is also immersed in a linguistic diversity. Some languages encode cultural concepts that cannot be directly translated into other languages. For example, the Japanese term “wabi-sabi” and the German term “Schadenfreude” have meanings too complex to translate directly – they require explanation more than translation. These kind of expressions may lead to false negative of the MT system that deteriorates translation quality. Human translators, on the other hand, can express meaning well by adapting natural language ploys such as context explanation and paraphrase.

To address these challenges, researchers have investigated approaches such as transfer learning [zoph2016transfer], multilingual NMT [haz] and data synthesis to improve machine translation for low-resource languages. While certainly promising, these approaches cannot yet completely substitute the deep linguistic understanding and cultural sensitivity that human translators bring to the table. As a result, hybridisation between the MT draft and human experience remains as the most effective methods for many language directions along with unpopular or low-resource ones. In conclusion, language

diversification reinforces a common shortcoming of MT systems. Low-resourced and culturally diverse languages need human assistance to maintain fidelity, contextuality and cultural sensitivity, whereas high-resourced languages benefit from fast accurate translations. An integrated methodic approach ensuring the effectiveness and quality in multilingual communication is to use machine translation (MT) with human translators.

C. Ethical Considerations

The increased application of machine translation (MT) raises several ethical questions that go beyond the technical issues related to performance. Data security and data privacy are the primary concerns. A lot of machine translation (MT) systems, usually cloud-based ones such as DeepL or Google Translate take the user content and run it on a remote server. There is a clear privacy issue when sensitive data, including financial statements, medical files, legal documents or private communications -- intentionally or not -- are stored incorrectly or inadvertently provided to others. Human translators, however, can guarantee sensitive or derogatory information is treated sensitively through strict confidentiality terms, secure offline settings and professional codes of ethics. Two more ethical issues are correctness and responsibility. In the case of a mistranslation in areas as medical translation, legal translation, technical translation, there could be grave consequences like inaccurate diagnosis, contract disputes or financial losses. Even if MT systems may produce unsystematic errors without prior warning, the users may accept the output as authoritative. This raises the question of accountability and responsibility: is it the company that uses the translation or the software vendor which is responsible for errors? When the translations involve humans, those individuals can provide explanations or make corrections that could reduce the chances of a very bad misinterpretation occurring, and they are likely to be held to professional standards of responsibility.

Another is job displacement. Concerns are raised that demand for expert human translators may drop, the faster and more accurate machine translation (MT) become and the further they penetrate into everyday life. While MT may enhance productivity, it can also threaten the economic survival of translators who perform translations that are typically considered first in high volume. This raises broader economic issues about retraining, labour adaptation, and fair distribution of the benefits of automation. Others, however, argue that MT changes the job description of human translators instead of replacing them entirely, with an increasing focus on post-editing and quality control, thus specialist translation tasks (which computers cannot be hired to perform). Ethics is also about cultural sensitivity. Unintentionally, MT systems can create offensive, abusive or culturally inappropriate translations. Politically sensitive material (racial or ethnic vocabulary, say, or gendered language) for example call for caution. It becomes harder for a human translator to manage these nuances, so translations align with cultural norms and values. Indeed, neural models trained on biased or unrepresentative datasets can perpetuate bias, strengthen dominant languages and diminish the voices of minorities; This problem is widely referred as algorithmic bias in machine translation.

Finally, two ethical aspects are transparency and informed consent. End Users should understand the risks and features of MT systems—particularly for any sensitive or high-stakes data. Organizations using MT should implement practices for human review, quality control and appropriate disclaimers in order to mitigate ethical concerns. Hybrid systems with machine translation and human quality are advantageous not only for quality improvement, but also resolve many ethical issues related to this worker group, making the workflow responsible and well-balanced. In conclusion, privacy issues, accountability concerns, employment displacement fears, cross-cultural sensitivity and AI bias are all ethical topics in MT. Such concerns can only be overcome with sound governance practices, the judicious combining of human capabilities, and an understanding of social and cultural effects of automation translation systems. In this way, organizations can resolve moral quandaries and maintaining high-quality translations with a combination of human judgment crossed with machine translation efficacy.

IV. USER PERCEPTIONS AND ACCEPTANCE

User perceptions have a large influence on the effectiveness, trustworthiness and adoption of MT systems. Speed and price are on the side of MT, acceptability largely depends on user trust in accuracy, cultural fit, and reliability. It is also reported that perception varies based on the environment used, type of user, and translation purpose. MT is appreciated by the majority of end users for being affordable, available and easy to use assuming that they are students, tourists or general readers. Users tend to tolerate some imperfections due to the fact, MT is assumed sufficient for small tasks (e.g. translating a few words in an email, site content or social media post). Enterprises, and professional translators on the other hand are more suspicious of MT. They recognize machine translation's potential to streamline repetitive, large-volume work, but remain skeptical of its effectiveness where complex, context-specific or subject-related text is concerned. Judicial and medical translators, for example, tend to prioritize accuracy and precision more than others do; consequently, they are more likely to use human-aided MT with extensive post-editing. In this same way, with companies using MT for public communications, literature or marketing materials, there is a fear of tone, style and cultural correctness—areas that MT falls short in frequently.

Perceived quality affects MT's credibility. It has been studied that fluent and natural MT outputs as well as the presence of errors in idiomatic expression or technical terms can influence user acceptance. If the MT service were anything other than in general good order, this could be problematic.” This underscores the need to use machine translation (MT) and human evaluation in concert with one another to ensure translations that meet both user acceptability and professional standards. Experience and previous interactions with MT are also factors shaping users’ opinions, regular use may lead them to trust MT effectiveness, while light-users become more critical. In addition, since users trust that quality and accuracy are ensured, contact with hybrid workflows (MT outputs post-edited by human translators) can contribute to confidence.

Culture-specific factors also impact acceptance. Due to previous bad experience with incorrect or less fluent translations, in multilingual settings and for low-resource languages users might be more skeptical towards the use of machine translation (MT). Users’ trust in the system, on the other hand, is likely to be higher for high-resource language pairs where adequately matured MT models are available. It is clear that perceptions are dynamic and contextual; this trend can be illustrated by the increasing adoption of user feedback in organization’s workflows for measuring MT performance and improving workflow integration. Finally, ethical shocks such as accountability, privacy and transparency impact user acceptance. Such MT systems that provide human-review options, disclaimers for critical content, and clear presentation of limitations are more likely to be trusted by the users. These concerns can be alleviated by the organizations to incentivize higher MT usage, satisfaction, and trust while maintaining ethics and quality. In summary, quality, context, experience, culture familiarity and ethics all play roles in how users perceive and adopt MT – for problem-solving confidence and accurate translation results, hybrid systems combining the efficiencies of machine with human expertise can work really well. To develop MT workflows that address the diverse needs of global audiences with respect to speed, cost and quality, it is important to be aware of user perceptions.

V. THE FUTURE OF TRANSLATION: HUMAN-MACHINE COLLABORATION

The development of machine translation (MT) technologies and the proliferation of neural machine translation (NMT) models are dramatically changing the practices in the language industry; at the same time, multilingual communication is increasingly required for global businesses. Despite how the advances of MT has brought us unprecedented levels of speed and cost-effectiveness, it still struggles with cultural appropriateness, idiomatic representation, and contextual understanding. However, the quality of HT is currently unbeatable in terms of its ability to translate meaning and style (intonation) between languages. The combination of the two—the wisdom of centuries versus the efficiency of machines—is where I believe lies the future of translation, illustrating how hybrid models may address the complex needs in current communication. In hybrid translation, that is Machine Translation Post Editing (MTPE), or human-in-the-loop translation, MT systems generate the initial drafts that then get edited, localized and improved by the human translators. In this joint model we can benefit from the advantages of both methods: MT for fast, high-volume translation and HT for the quality, cultural aspects and stylistic integrity. For instance, MT performs well with formulaic and repetitive data in technical materials so that human translators can focus on domain-specific terminology, idioms, and context-dependent text. Productivity climbs sharply without any loss in translation quality when labor is divided this way in a hybrid workflow.

One of the key advantages of people working with machines, is their rapid way to strike a balance between speed and accuracy. Though it is correct, human translation can be lengthy and laborious, especially for projects with massive amounts of content and imminent deadlines. MT can perform these high-volume operations and easily come up with draft translations in a fraction of the time. Then post-editing is performed by human translators who correct semantic errors, polish sentence structures and cater the style to the target readers. Studies also report that MTPE can produce outputs with quality as good as human-only translations when the MT systems are put to task and the hypothesized post-editors are competent (PLOS, 2023). This hybrid solution retains the temporal and cost-benefits of automation, but offers a response to contextual and cultural appropriateness – one of machine translation’s main points. Further more, the domain specific translation quality can be enhanced by human-machine collaboration. Accurate terminology and consistent style are extremely important in specialized sectors such as marketing, technology, medical and legal. Translations from general MT-trained corpora can be stylistically wrong or misunderstand technical vocabulary. Human translators, due to their subject knowledge, ensure that the language is used appropriately, context maintained and communication goals achieved. The high demands of workflow in essential and professional settings can be met by generating scalable and sustainable translations that combine the human quality with machine speed.

The future of translation, as well, is learning and adaptation. To enhance future performance, hybrid workflows facilitate feedback loops letting the changes made by human post-editors be fed back into MT systems. Due to this iterative procedure which optimizes ML models, MT systems can eventually understand complex syntactic forms, rare terms and idioms far better than in the early days. As a result, a symbiosis between human intelligence and AI is established since

human translators improve the quality of translations while contributing to the building of MT systems. Cultural and moral surveillance is an important aspect of the human-machine relationship. MT systems can inadvertently output culturally insensitive, biased, or gendered content. To avoid any translations that do not comply with social, cultural and moral conventions, it is necessary for human translators to recognize and correct these mistakes. Wherever there are legal documents, public communications, international marketing and diplomatic contexts (in which even the most slight mistakes or insensitivity could be severely consequential), control will be crucial. Thus, hybrid models respect professional and ethical constraints in translation processes and at the same time improve their efficiency and quality.

Hybrid translation contributes not only to solving technical and ethical problems, but also towards the promotion of accessibility and diversity in international communication. In addition to the human translators ensuring that their work is clear, accurate and culturally appropriate, companies will attempt to cast a wide net in as many languages as possible (even minority or less-resource rich ones) by using machine translation (MT) reach out quickly. This democratization of translation promotes intercultural communication, simplifies the exchange of multilingual information and increases the participation in social media, education, business or governance around the world. So in other words, it's going to be difficult for humans working together with machines efficiently. A pragmatic, effective and sustainable solution to the issues created by digital communication, globalisation and increased demand for multilingual material can be found in hybrid translation models. Companies and translators can develop high-quality translations that meet a variety of demands by leveraging MT for velocity and scalability in conjunction with HT for precision, context, and culture. Moreover, the MT system itself is iteratively improved over time through the iterative learning from human feedback, leading to a win-win and dynamic cooperation. With the advancement of technology, it will bring a new orientation to international communication and change the image of translation with high ethical responsibility, efficiency and quality becoming primary before us.

VI. CONCLUSION

Machine translation (MT) and human translation (HT) are two complementary means of surmounting linguistic and cultural barriers in international communication. Quality of these translation methods, difficulties in using them and user opinions have been compared in the research along with pros and cons of each method. Especially with complex texts such as legal documents, the literature, technical manuals and culturally sensitive information, humans simply trump them in reliability, integrity and contextual understanding. Their competence enables them to maintain stylistic continuity, interpret colloquial expressions, and refine translations for all readers. MT, on the other hand, is faster and more scalable than anything else, and less costly - this where it's ideal for giving you an early return on large translation projects anyway for drafts or situations when volume is more important than accuracy. Artificial intelligence and neural machine translation (NMT) have progressed rapidly, nevertheless ambiguity, polysemy, syntactic complexity and cultural idioms continue to challenge MT. The effectiveness of MT is also limited by dialectical divergences, low-resource languages as well as specialized vocabulary. The broader implications of MT adoption can be found in ethical concerns concerning, for example, algorithmic unfairness, data privacy or employment displacement. Human supervision is necessary in translation processes, not only to assure precision, cultural relevance and ethical propriety, but also the respect of regulations. In addition, user perception on MT illustrates that although cost and ease of use are desired, reliability and finetuning is still a key issue.

Human-machine collaboration is the most hopeful research reaching for. The advantages of the two strategies are merged in hybrid systems, which exploit HT knowledge and MT efficiency. Whereas human translators refine, elaborate and ensure accuracy and cultural sensitivity, machine translations generate draft versions quickly. Preserving sound outputs, this collaborative framework enhances speed, scalability and efficiency. In addition, human PE input keeps the MT systems learning and developing, so there is a perpetual loop of learning which incrementally improves performance). In addition to addressing ethical and cultural concerns, hybrid translation addresses these challenges by minimizing bias, safeguarding sensitive data, and ensuring that translations are socially and culturally appropriate. On top of that, hybrid translation also democratizes a multilingual content both from the consumers' point of view and for those in business who target various language speaking users. Organizations can maintain global involvement, support educational curricula and enhance the empathy of responsiveness by integrating MT with HT. Given the growing demands of a multilingual communication, in particular at professional and digital level, this integrated solution seems worthwhile, useful, productive.

In conclusion, MT and HT are better seen as mutually complementary aspects of a modern translation ecology than opposed to each other. HT offers high precision and context or culture-sensitivity, but it is slow, heavy to manage and expensive: MT allows the communication service faster, scalable, low cost. The future of translation belongs to the cooperation between humans and machines, which provides a model that is ethically justified, suitable to change and capable of balancing different requirements for international communication. For the best results, organisations, schools, translators and lawmakers need to know the pros and cons of both approaches, work with hybrid workflows when suitable, and periodically evaluate translation quality. By combining state-of-the-art technology with human judgement, the

translation industry is uniquely poised to deliver high quality, culturally sensitive and effective cross-language communication. This will do much to foster greater unity and inclusiveness for the world.

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