Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 4, 1007-1025
2024
Publisher: Learning Gate
DOI: 10.55214/25768484.v8i4.1478

Human-Machine Interaction Translation under Artificial Intelligence and Big Data: Analysis from the Perspective of Text Stratification and Corpus Construction

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Abstract: With the continuous advancement of artificial intelligence and big data technologies, the neural network-based machine translation driven by deep learning continues to flourish. This ongoing progress not only propels the application of translation technology and reshapes the translation industry but also profoundly impacts the realms of language learning and translation. This paper, situated against the backdrop of artificial intelligence and big data, focuses on the fundamental aspects of text stratification and corpus construction. Building upon discussions about text stratification and corpus construction, this paper extensively examines how human and machine interaction can effectively balance translation quality and cost, maximizing translation efficiency. Additionally, this paper proposes several innovation suggestions regarding future bilingual translation pedagogy.
Keywords: *Artificial Intelligence, Corpus construction, Human translation, Machine translation, Text stratification.*

1. Introduction

The rapid advancements in technologies like artificial intelligence (AI) and big data are driving transformative shifts within the language service industry (Liu et al. 2023) [1]. Language intelligence products, exemplified by ChatGPT, have inaugurated an era of human-machine interaction, profoundly influencing the cross-cultural communication and the knowledge dissemination (Hu and Qi 2023) [2]. Machine translation technology, as a pivotal branch of artificial intelligence (Ai 2022) [3], perpetuates the trends in promoting the application of translation technology, reshaping the translation industry, and deeply impacting language acquisition and translation practices (Kenny 2022) [4]. With globalization deepening, the escalating interactions between China and other countriess worldwide engender an incessantly growing demand for various text translations, surpassing the capacity of traditional manual translation to meet the burgeoning translation needs (Doherty 2016) [5].

Compared to human translation, machine translation possesses various advantages such as faster translation speed, greater translation capacity, lower translation costs, and support for multilingual translation at the same time (Guerberof 2008; Flournoy and Duran 2009; Groves and Schmidtke 2009) [6-8]. However, current fully autonomous machine translation technology remains immature, making it challenging to generate high-quality translations without human intervention (Bowker 2019) [9]. This is due to the shortcomings of machine translation, including inadequate accuracy and professionalism in certain fields, and existing technical limitations like erroneous recognition (Yamada 2015) [10]. To ensure translation quality, the machine translation process cannot entirely detach from human involvement (Wang and Daghigh 2023) [11].

The human involvement in machine translation primarily manifests in pre-editing and post-editing (Wang and Wang 2019) [12]. Pre-editing refers to preprocessing the target text before machine translation to ensure a higher level of the source language text (Yang and Wei 2023; Rei and Atsushi 2021) [13,14]. Post-editing involves processing and modifying the primary output of machine translation according to specific objectives and requirements (Rico and Torrejon 2012; Feng and Liu

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2018; ÇETİNER 2021) [15-17]. Both pre-editing and post-editing compensate for translation errors in machine translation, allowing human-centered pre-editing and post-editing to integrate humanistic, cultural, and customary factors that machine translation lacks. Pre-editing and post-editing by humans are not only social activities, constrained by translation standards, ideologies, and professional ethics, but also intricate cognitive processes, subjected to cognitive and psychological control (Wang and Wang 2023) [18]. In the era of artificial intelligence, the proficiency of translators in pre-editing and post-editing becomes a crucial part of their professional competence, so the development of pre-editing and post-editing capabilities is indispensable in cultivating translation talents at the age of artificial intelligence and big data.

Moreover, with the advent of economic globalization and social informatization, the number of the text's translation requirement are daily growing and the forms of texts requiring translation are becoming increasingly diverse. Consequently, different industries and groups have presented distinct demands regarding the quality of translated texts. By analyzing the demands within the commercial translation market, it can be found that various text types and materials have distinct quality requirements for the translated text owing to their diverse usage purposes. As a result, different translation strategies such as machine translation, human-machine interactive translation, or pure human translation can be chosen to achieve the optimal balance among cost, efficiency, quality, and user satisfaction. In the era of artificial intelligence, the synergy between computers equipped with deep learning capabilities and human expertise will likely yield highly efficient and superior translations (Zong 2018) [19].

Given the aforementioned analysis, this paper aims to find a way for human and machine to interact with each other at the backdrop of artificial intelligence and big data. This paper takes the text stratification as a way to separate the role of human and machine, further proposes employing distinct translation strategies, either dominated by human intervention or machine-driven, corresponding to these different text levels. Additionally, this paper envisions the establishment of translation corpus, and the objective is to explore feasible and intelligent approaches for translation machine to deep learning by themselves, in order to enhance the "thinking ability" of machine translation continually.

The primary contribution of this paper lies in its exploration, within the context of artificial intelligence and big data, of stratification in translation texts and the possible assumption of corpus construction suitable for machine translation. Building upon the integration of text stratification and corpus construction, the paper deliberates on the delineation of roles and collaboration between human and machine in the translation process to optimize translation efficiency. Furthermore, the envisioned proposals in this paper suggest recommendations for future translation talent cultivation according to the concepts this paper put forward.

The framework of this paper is outlined as follows: Section 1 introduces the background of this paper, and Section 2 comprises a literature review and outlines the main hypotheses of this paper. Section 3 proposes a hierarchical structuring of texts and delineates suitable translation strategies for various hierarchical levels. Section 4 discusses the potential and necessity of building corpus in the context of artificial intelligence and big data. Section 5 elaborates on the roles of both human and machine in accordance with corpus construction and text stratification. Finally, Section 6 concludes this paper and presents potential approaches for cultivating translation talents in the future.

2. Research Background and Theoretical Assumption

2.1. Machine Translation

Machine translation, also known as automatic translation by computer, refers to the process of using computers to convert one natural language (source language) into another natural language (target language) (Poibeau 2017, 7-8) [20]. Traditional machine translation systems can be categorized into two main types: rule-based and corpus-based. Presently, the predominant approach in machine translation relies on neural network-based translation (Zhang et al. 2023) [21]. Figure 1 is the history of the machine translation development.

ISSN: 2576-8484
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DOI: 10.55214/25768484.v8i4.1478

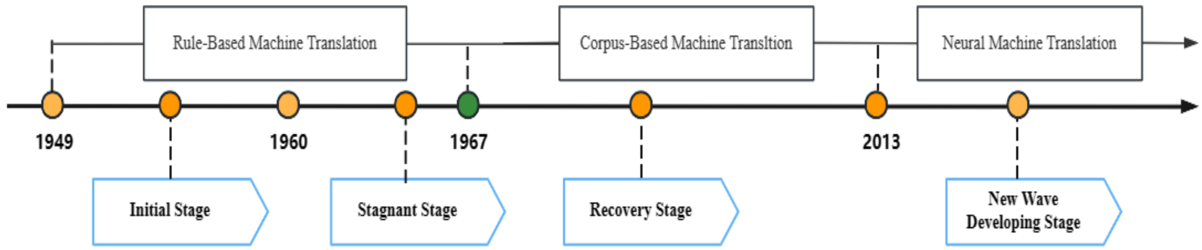

Figure 1.
Evolution of machine translation[1].

2.2. Rule-Based Machine Translation

Rule-based machine translation is grounded in machine dictionaries as knowledge sources (Yu and Bai, 2014) [22], and human translation experts provide linguistic rules enabling machines to perform automatic translation (Hutchins, 2007) [23]. The linguistic rules encompass syntactic, semantic, and knowledge-based regulations. The crux of rule-based machine translation lies in constructing a high-quality repository of translation rules. Rule-based machine translation's advantage lies in independence from corpus, yet its drawback resides in the limited coverage of translation rules, struggling to exhaustively describe the myriad linguistic phenomena and extralinguistic common knowledge with a finite set of rules (Terumas, 2007) [24].

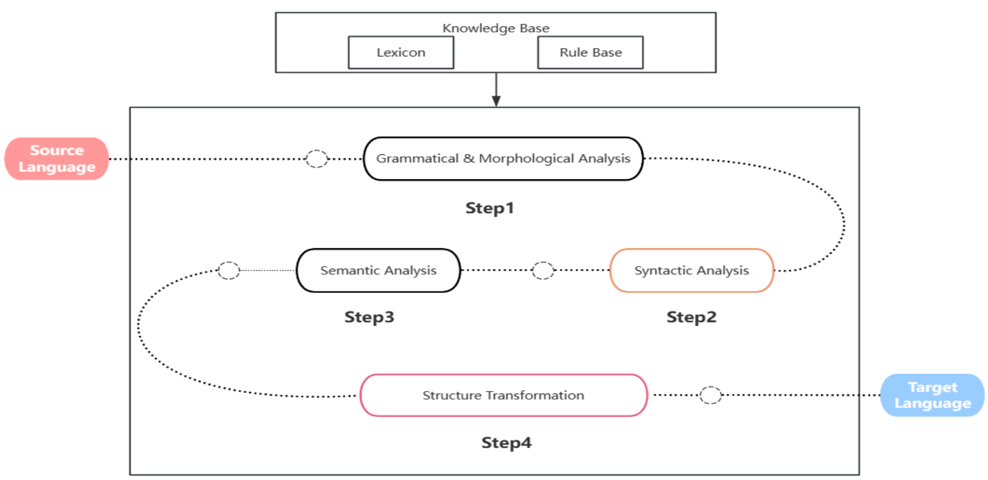

Figure 2.
Rule-based machine translation flowchart[2].

2.2.1. Statistic-Based Machine Translation

Statistic-based machine translation, also known as corpus-based machine translation, relies on extensive parallel corpus and preprocessing techniques (Tian et al. 2014) [25]. The characteristic of predominantly being driven by data and statistical regularities can help to overcome difficulties in acquiring translation rules and knowledge sources (Hinton et al., 2012) [26]. Common statistic-based

[1] This picture is derived from paper *A Survey of Neural Machine Translation* by Zhang et al. in 2023.
[2] These pictures describe the rule-based machine translation flowchart which concluded from Hutchin's paper *Machine Translation: A Concise History* in 2007.

machine translation approaches include: 1) word-to-word alignment translation, 2) phrase-to-phrase alignment translation, and 3) syntax-to-syntax alignment translation. The advantage of statistic-based machine translation lies in its reliance on data-driven approaches, effectively utilizing prior knowledge. However, the drawback lies in its dependence on vast corpus.

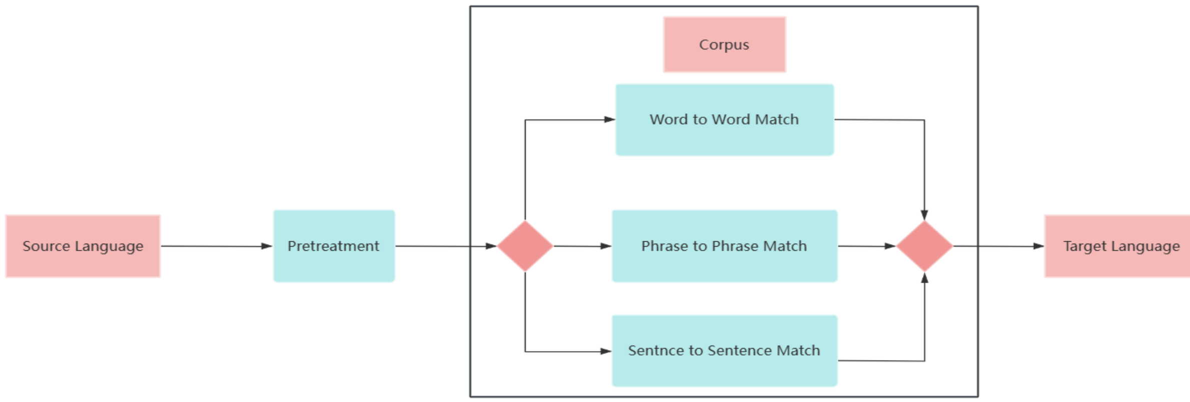

Figure 3.
Statistic-based machine translation flowchart[3].

2.2.2. Neural Network-Based Machine Translation

Neural Machine Translation (NMT), based on artificial neural networks, revolves around a deep neural network with an extensive number of nodes (neurons), capable of autonomously acquiring translation knowledge from corpus. Neural network machine translation typically adopts an encoder-decoder structure (Cho et al. 2014) [27], enabling modeling of variable-length input sentences (Sutskever et al. 2014) [28]. The encoder comprehends the source language sentence, forming a specific-dimensional floating-point vector. Subsequently, the decoder generates the target language translation based on this vector. Initially, in the early stages of neural network machine translation, recurrent neural networks (RNNs) were widely employed as the network structure for both the encoder and decoder (Sutskever et al. 2014) [28]. RNNs excel in modeling natural language. Represented by long short-term memory networks (LSTMs) and gated recurrent unit networks (GRUs), RNNs use gating mechanisms to "remember" crucial words, allowing for longer "memory" retention (Chung et al. 2014) [29].

In 2017, convolutional neural networks (CNNs) and self-attention networks (Transformers) were adopted as decoder and encoder structures (LeCun et al. 2015; Meng et al. 2015; Gehring et al. 2017; Vaswani et al. 2017) [30-33]. Not only did they surpass RNN neural networks in translation performance, but they also enhanced training efficiency through parallelization during training. Presently, the predominant framework in the industry for machine translation relies on self-attention networks (Transformers).

The neural network machine translation system relies on bilingual or multilingual parallel corpus data for translation. These systems are entirely empirical, employing deep learning from corpora to achieve machine translation, abandoning entirely the symbolism approach based on language rules. The advantage of this system lies in its ability to enhance translation quality, albeit reliant on extensive corpora. Therefore, the construction of vast corpora becomes particularly crucial.

[3] This pictures describe the statistic-based machine translation flowchart which concluded from Hinton's paper *Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups* in 2012.

DOI: 10.55214/25768484.v8i4.1478

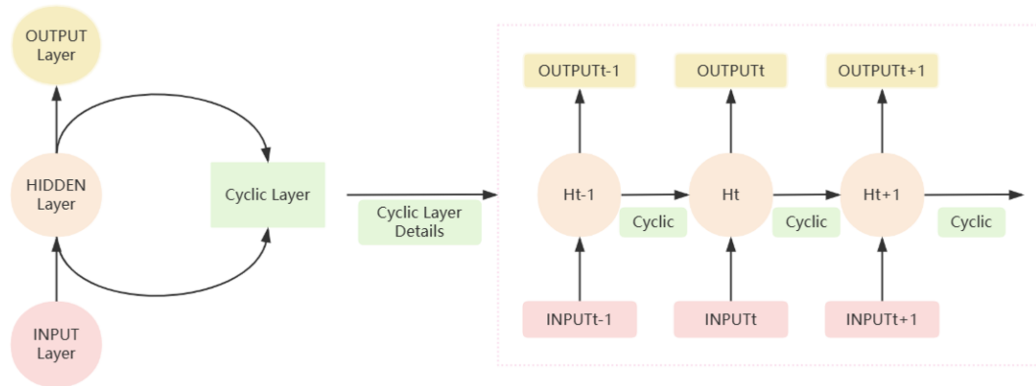

Figure 4.
Neural machine translation flowchart (Takes RNN as an example)[4].

2.2.3. Machine Translation in Artificial Intelligence Era

In the 1970s, machine translation was designated as a significant subject of artificial intelligence research. In the era of big data, with the advancements in artificial intelligence technology, translation techniques experienced rapid development. Under the umbrella of AI, machine translation of textual content primarily comprises two elements: neural network systems and corpus.

Although the developmental trend of machine translation based on neural network systems within the context of big data is promising, certain issues persist (Jiang and Lu 2020) [34]. Firstly, due to the data-driven nature of neural network machine translation, the size and quality of corpus significantly influence translation results. The current establishment of corpus remains incomplete, with many words yet to be covered by existing corpus (Robbie 2020) [35], particularly specialized terms, newly added internet vocabulary, and specific abbreviations. Secondly, while neural network machine translation primarily focuses on sentence-level translation, the quality of translated texts for discourse-level translation remains to be evaluated. Thirdly, the rise of large-scale language models alongside neural network models involves extensive parameter learning, enabling these large models to acquire finer-grained knowledge, thereby enhancing the generalization and expressive capabilities of neural network models, but the existing corpus lack sufficient datasets to meet the training demands of those models.

In conclusion, machine translation, as a product of technological advancement, indeed plays a significant role in fostering contemporary cross-cultural and cross-linguistic activities. However, due to the incompleteness of corpus and varying quality requirements for different texts, coupled with the fact that machine translation lacks autonomous consciousness, machine itself cannot comprehensively consider the humanistic and cultural factors within texts. Hence, human intervention in the translation process remains a necessary condition following machine translation.

2.3. Pre-Editing and Post-Editing

The rapid development of globalization and information technology has propelled the translation industry. However, current machine translation technology remains immature (Kenny 2018) [36]. To ensure the quality of translations, human intervention in editing before and after machine translation is necessary, with pre-editing and post-editing serving as compensatory measures for enhancing machine translation quality (Arenas 2019) [37].

Pre-editing primarily refines the text before machine translation, often involving formatting and linguistic adjustments. This process aims to elevate the text's quality pre-translation, making it concise

[4] These pictures describe the statistic-based machine translation flowchart which concluded from paper *Neural Machine Translation by Jointly Learning to Align and Translate* by Bahdanau et al. in 2014.

and controllable, thus aiding machine comprehension and analysis. This, in turn, enhances the accuracy and production quality of machine translation (Miyata and Fujita 2021) [38]. Positioned as an upstream process in machine translation, pre-editing can preprocess and control the source text. Effective pre-editing significantly reduces the workload for post-editing (Cui and Lei 2016) [39]. Post-editing refers to the process of modifying the original machine-translated output according to specific objectives and requirements to enhance the accuracy and fluency of machine-translated texts (Feng and Cui 2016; Liang and Han 2022) [40,41].

Both pre-editing and post-editing aim to present better translation quality (Miyata and Fujita 2021; Liang and Han 2022) [14, 41]. Currently, machine translation cannot entirely replace human translation. Translation is a complex intellectual activity of humans, involving not only the internal structure of languages but also diverse factors external to language: everyday life knowledge, societal knowledge, historical knowledge, cultural background, specialized disciplinary knowledge, the psychological state of individuals when writing, emotional desires (Taule et al. 2022) [42]. All the other factors but not language itself collectively form the "humanity core" of translation.

Even currently, humans cannot directly observe the cognitive thinking operations within the "black box" of the brain (Robinson 2021) [43]. All brain information processing activities remain secretive and intricate. Consequently, neural network machine translation also cannot handle the cognitive thinking required in the translation process. Hence, human involvement remains indispensable throughout the entire translation process (Miyata and Fujita 2021) [14].

Chinese mathematician and linguist Zhou Haizhong (1992) [44] also emphasizes that to enhance the quality of machine translation, the primary concern should address language itself rather than just programming design. Solely relying on programs cannot enhance the quality of machine-translated texts. Furthermore, Zhou (1992) [44] highlights that until humanity comprehends how the brain performs fuzzy recognition and logical judgment in language, achieving simultaneous fidelity, expressiveness, and elegance (faithfulness, expressiveness, and elegance) in machine translation is unattainable. Thus, humans play an irreplaceable role in both pre-editing and post-editing in machine translation.

According to the *Language Services Market: 2016* reported by the US-based Common-Sense Advisory, machine translation post-editing accounts for 3.94% of the entire language service industry market. Among language service providers, 25.39% offer post-editing services, perceiving it to have broad market prospects [45].

In summary, both pre-editing and post-editing involving human intervention represent a complex cognitive task. The process encompasses a series of intricate cognitive activities such as understanding the source text, language coding conversion, and translation revision (O'Brien, 2017) [46]. In recent years, with the continuous advancement of artificial intelligence, post-editing has gradually garnered attention, with many scholars exploring post-editing from a cognitive process perspective. However, from both ethical and technical perspectives, machines lack the capability for self-thought. Machine comprehension of text is limited to surface-level analysis and cannot consider the text's meaning comprehensively from social, historical, and cultural aspects. Therefore, human involvement remains necessary throughout the process of machine translation (Zong, 2018) [19].

2.4. Human-Machine Interaction Translation Model Assumption

The neural network machine translation has significantly boosted translation efficiency, ushering in the era of artificial intelligence in machine translation. In the age of artificial intelligence, technological advancements compel translators to reassess the connection between machine translation and human translation (Lihua 2022) [47]. Building upon the literature on machine translation and human editing, this article analyzes and proposes a conceptual framework for the joint participation of humans and machines in the translation process.

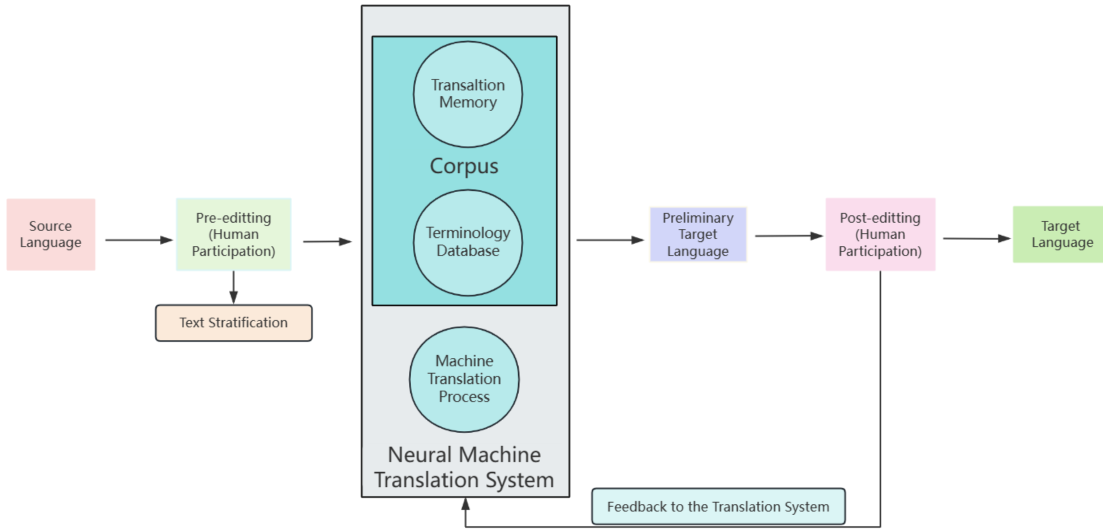

Figure 5.
Human- machine interaction translation model assumption[5].

The steps of the human-machine interactive translation model are as follows: 1) Translators conduct pre-translation processing on the source language to render the text concise and manageable, facilitating machine analysis; 2) The translated text is inputted into the machine translation system, enabling the machine to match and analyze the text using the system's translation memory, terminology database, and translation dictionaries, producing preliminary translated text; 3) Translators engage in post-editing of the machine-generated preliminary translation to form the final translated text.

Moreover, the text from post-editing not only constitutes the final text but also requires feedback to the machine translation system for its self-learning. In the process of post-editing, the modified information is fed back to the neural network translation system. On one hand, the system needs to recognize and utilize this feedback information to continuously enhance its own translation knowledge base, avoiding reproducing the same errors in the future. On the other hand, this feedback information can be stored in the translation memory, becoming part of the corpora, continually training the machine, enabling its self-learning to generate more language units. This allows the machine to better adapt to human language rules and serve text translations more effectively (Cai et al., 2021) [48].

2.5. Text Stratification in Human-Machine Interaction Translation

2.5.1. What Significance Does Text Stratification Hold?

Text stratification in this paper refers to the classification of the text to be translated into different levels based on the type of text, its intended use, quality requirements for the translation, and constraints related to translation costs. In today's societal context, the purpose and usage of diverse translation materials vary, where translation quality is no longer the sole measure of translation. Determining the success of a translation involves numerous factors, including translation quality, time spent on translation, and the translation budget. Effective translation aims to strike an optimal balance among these factors.

With the ongoing development of economic globalization, numerous industries have translation needs. It is particularly crucial to "treat differently" to various texts based on the intended usage of the translated text and the corresponding quality requirements. For instance, some texts require simple

[5] This pictures describe the Human- Machine interaction translation model assumption in the context of text stratification and corpus construction under big data and artificial intelligence.

DOI: 10.55214/25768484.v8i4.1478

information retrieval, where the translation only needs to be comprehensible to those seeking information, thus demanding lower translation quality. On the other hand, certain texts aim for accurate information, serving guiding, communicative, or promotional roles, necessitating moderate translation quality that includes precise terminology, coherent expression, and faithfulness to the original text. Furthermore, certain texts aim to convey the thinking and emotions of the source language, fulfilling educational, aesthetic, explanatory, standardizing, or economic roles. These texts, in addition to accurate terminology, fidelity to the source text, and coherent sentences, also require the translator to adhere to the specific expression habits of the target language and correspond to the specific thinking patterns of the target language audience. Such texts impose higher demands on the translator's subjective initiative and thinking process.

2.6. The Stratification of Text

Machine translation is the major trend in the future translation market. A Scholar noted as early as 2013 that a pyramid-shaped translation market was emerging, wherein a cost-constrained translation model was forming. Only 10% of translation tasks necessitated complete human translation, while 70% of documents required a combination of machine translation, with the remaining 20% of texts utilizing post-editing for translation (Du et al. 2013) [49]. In addition, Chen (2020) [50] put forward that AI translation will gradually increase its market share in the future. Regarding the categorization of different texts, this paper adopts the classification proposed by Chinese scholars Cui and Lei (2016) [39], dividing texts involving translation into three levels: reference-level texts, standard-level texts, and publication-level texts.

Reference-level Texts. Reference-level texts constitute a substantial category found in people's daily lives and work environments. Particularly, with the continuous evolution of information networks, the fragmented texts proliferate explosively on the internet, leading to a considerable demand for the translation of such texts. However, the primary purpose of translating these texts is to obtain basic and simple information, catering to users who don't require precise meanings but rather a general understanding. Reference-level texts emphasize immediacy, where users often seek immediate access to translated content. These texts encompass instantly generated content on social platforms, real-time information available on web pages, and cross-language dialogues emerging instantly on cross-border trading platforms.

Standard-level Texts. With the continuous advancement of globalization, the increasing exchanges between China and other nations encompass cultural, technological, and economic interactions. Language, serving as a medium in these exchanges, plays a pivotal role. Hence, the translation quality of texts related to these interactions requires careful consideration. Standard-level texts refer to texts employed in various international communications, mainly practical texts spanning diverse sectors of societal development. They include user manuals or instructions within specialized fields such as technology, machinery, sports, patents, aerospace, biology, architecture, trade conventions, alongside news releases, economic reviews, and social commentaries. The primary objective of these texts is to provide standardized explanations and disseminate information. When translating such texts, accuracy in conveying meaning is essential. Additionally, attention must be paid to domain-specific terminology. Given the different stylistic expressions across various fields, translations of these texts need to adhere faithfully to the linguistic style specific to the text's actual type and ensure equivalent terms in the target language.

Publication-level Texts. Publication-level texts primarily refer to literary and artistic works, political and religious texts, legal regulations, and scientific treatises. These types of texts demand extremely high translation quality and are often used for publication by press. Translations of literary and artistic works aid individuals from different cultural backgrounds in understanding historical events and societal phenomena from other cultural perspectives. They foster empathy across diverse cultures, refine sensibilities, and enlighten intellects, possessing high artistic value. Poor-quality translations can easily lead to misunderstandings about different cultures and garner negative evaluations of the author's creative inspiration and ideas from the source text. Political and religious texts convey a society's values and beliefs. In addition, these texts are generally sensitive, and even minor translation errors can provoke widespread discussion and controversy. Legal regulations encompass statutes, regulations and so on, characterized by distinct vocabulary, syntax, and stylistic features. Texts related to law possess mandatory, stringent, and normative aspects. Translating legal texts requires meticulous attention as a slight discrepancy in wording might result in significant economic losses and irreparable consequences. Scientific treatises demand translations based on objective facts and truthfulness. Errors in translating such texts can impede scientific progress and may even lead to irreversible outcomes.

2.7. Matching Text Stratification with Translation Strategy

Hans Vermeer's Skopos theory of translation asserts that translation is an action driven by specific purposes. The intended purpose or function of a translation determines the methods and translation strategies employed (Hans and Andrew 2021) [51]. The "Skopos rule" stands as the primary rule to be followed in all translation endeavors. Chinese scholars like Cui Qiliang, based on the Skopos theory, argue that for different levels of texts, translators or project leaders should adopt corresponding translation strategies based on varying translation purposes and quality requirements. Furthermore, they possess the authority to decide which content from the source text can be retained and which needs adjustments or modifications based on the translation purpose.

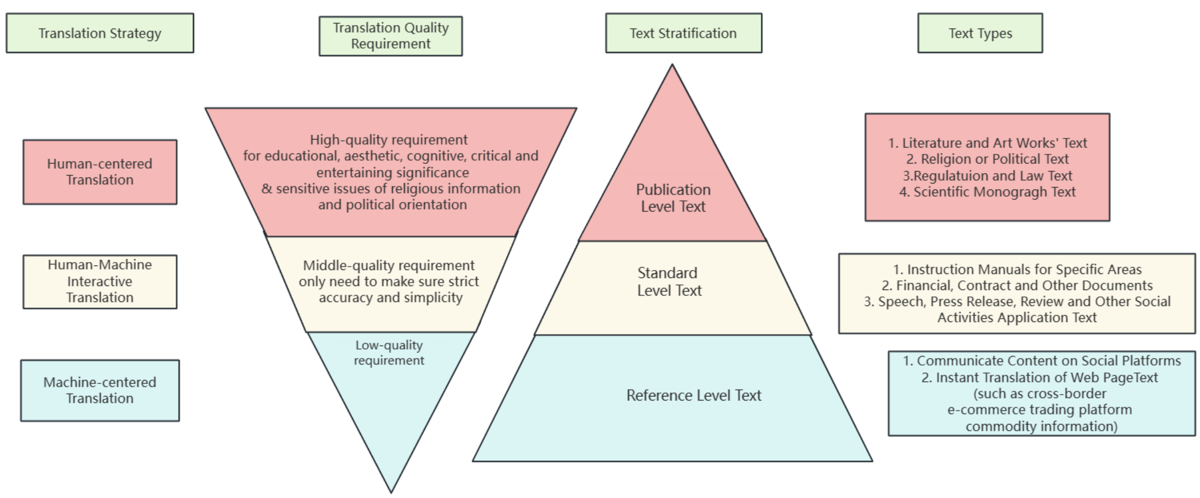

Figure 6.
Text stratification and translation strategies[6].

For reference-level texts, the purpose primarily revolves around basic information acquisition and exchange. Translating reference-level texts merely requires conveying the general meaning with a focus on immediacy. Given the low-quality demand for these texts, a translation strategy primarily driven by machine translation can be adopted. For instance, translating media texts like text messages, emails, social media posts, online shopping platforms, and forum threads falls under this category. These texts are abundant, diverse, often deviate from grammatical norms, possess colloquial content, and emphasize spontaneity and real-time expression. Due to the low requirement for translation quality in these texts, fully autonomous machine-based automatic translation can be employed.

[6] This picture describes the details of text stratification and the translation strategies adopted in different text layer.

DOI: 10.55214/25768484.v8i4.1478

Example 1: The product introduction in eBay office website

About this product

Product Identifiers

Brand	Apple	MPN	MWP22ZP/A, MWP22ZA/A, MWP22TY/A, MWP22AM/A, MWP22LL/A, MWP22RU/A
GTIN	0190199246850	UPC	0190199246874, 0190199247017, 0190199246850, 0190199246966, 0190199246935
Model	Apple AirPods Pro	eBay Product ID (ePID)	10034976643

Product Key Features

Color	White	Wireless Technology	Bluetooth
Connectivity	Bluetooth	Form Factor	In-Ear Only
Features	Water-Resistant, Speech-detecting accelerometer, Rechargeable Battery, Noise Cancellation, Sweat-Proof, Motion-detecting accelerometer	Microphone Type	Built-In
Number of Earpieces	Double	Type	Canal Earbud (In Ear Canal)

Additional Product Features

Manufacturer Color	White	Release Year	2019

Figure 7.
Product introduction of apple air pods pro on eBay official website[7]

关于本产品

产品标识符

品牌	苹果	MPN（MPN）	MWP22ZP/A、MWP22ZA/A、MWP22TY/A、MWP22AM/A、MWP22LL/A、MWP22RU/A
全球贸易项目代码	0190199246850	刚果爱国者联盟	0190199246874, 0190199247017, 0190199246850, 0190199246966, 0190199246935
型	苹果AirPods Pro	eBay 产品 ID（ePID）	10034976643

产品主要特点

颜色	白	无线技术	蓝牙
连接	蓝牙	外形尺寸	仅限入耳式
特征	防水、语音检测加速度计、可充电电池、降噪、防汗、运动检测加速度计	麦克风类型	内置
听筒数量	双	类型	耳道式耳塞（耳道内）

其他产品特性

制造商颜色	白	发行年份	2019

Figure 8.
Product introduction translation of apple air pods pro on eBay official website[8]

From example 1, it's evident that for reference-level texts, translation can be entirely accomplished by machines independently. Such text levels don't require human intervention in providing pre-editing or post-editing, significantly saving on labor costs.

For standard-level text, the translated text of this kind tends to be instructive, guiding translated service seekers from different language backgrounds to navigate their actions based on the translated content, aiming to achieve their intended objectives. These texts encompass practical information across various fields like tourism, economics, IT, patents, telecommunications, automotive, aerospace, biology, medicine, architecture, among others. And the translation should faithfully reflect the actual expression in the source language text, ensuring equivalence in terminology between the source and target

[7] This picture comes form https://www.ebay.com/, and this page mainly introduces the information about Apple Airpods Pro.
[8] This picture comes form https://www.ebay.com/, and this page mainly includes the information about Apple Airpods Pro, and was directly translated by machine itself.

languages, maintaining a consistent style with the specific text. For instance, in international trade contracts, the translation requires strict accuracy and conciseness, employing professional vocabulary and adhering to normative stylistic standards.

Example 2: Excerpt from a random International Contract Clauses

Source Language： 买卖双方同意按下列条款购买，出售下述商品，并签订合同。

Machine Translation: The buyer and seller agree to purchase and sell the specified goods according to the following terms and to sign a contract.

The Standard Translation in CISG[9]: This contract is made by and between the Buyer and the Seller, whereby the Buyer agrees to buy and the Seller agrees to sell the under-mentioned commodity according to the terms and conditions stipulated contracts.

Analysis: This sentence is a common clause in Contract. From the perspective of structure, language, clarity, terms, and formality, the second sentence can absolutely be presented in a contract, providing more detailed information, professional terms, and formal expression, which clarifies the nature of the contract and the roles of the buyer and seller, and it should be necessary for legal or formal documentation. Whereas the first expression seems too much concise in a contract, and not so professional.

For publication-level text, human translators have addressed the political and ideological factors more tactfully while the working mechanism of the neural machine translation system lacks the former's judgment, consideration, flexibility, and subjectivity. Moreover, unlike human translators, the neural machine system is not capable of activities such as summarizing the source texts, making comments or annotating (Sheng and Kong 2023) [52]. This section takes literary works as an example to illustrate the humanity core that related to ideological factors. The purpose of translating literary and artistic works is to convey aesthetic enjoyment and sophisticated entertainment based on social and humanistic factors, requiring a higher standard for the translated text. Although machine translation has advanced to recognize emotional factors within text (Guo 2022) [53], emotional recognition within text can be considered a content-based classification issue, involving concepts from Natural Language Processing (NLP) and the field of Deep Learning in Deep Learning-assisted Semantic Text Analysis (DLSTA) that proposes the use of big data for human emotion detection, and emotional detection from the source text utilizes concepts from natural language processing. However, this emotional detection relies on the presence of "emotional words" as cues for machines to identify such content, yet many literary texts employ nuanced vocabulary to describe emotions. The following discussion employs the translation of the literary work *Dream of the Red Chamber* to explore this further.

Example 3: Excerpt from the first chapter of Dream of the Red Chamber written by the author Cao Xueqin[10] titled The Story of the Stone.

Source Language:

满纸荒唐言，一把辛酸泪。

都云作者痴，谁解其中味。

Machine Translation:

Full of absurd words on the paper, tears of bitterness shed. They say the author is foolish, who can understand the sentiments within?

Famous Translator David Hawkes' [11]Translation:

This is a random example chosen from United Nations Convention on Contract for the International Sale of Goods.[9]

Cao Xueqin is an novelist, poet and painter in Qing Dynasty, and he is the author of Dream of the Red Chamber. The Dream of Red Chamber [10] is Cao Xueqin's great contribution to Chinese literature and Chinese culture, and the novel is a literary work based on Cao Xueqin's personal experience.

David Hawkes is an famous translator. In 1970, Hawkes seized the opportunity to cooperate with Penguin Press to fully start translate the [11] Dream of Red Chamber. Hawkes' Translation of Dream of Red Chamber was a groundbreaking event because there was no any English Version of Dream of Red Chamber in Western World.

Pages full of idle word
Penned with hot and tears
All men call author fool
None his secret message hears

Example 4: Excerpt from the first chapter of Dream of the Red Chamber written by the author Cao Xueqin titled Won-Done Song.

Source Language:

世人都晓神仙好，惟有功名忘不了。
古今将相在何方？荒冢一堆草没了。
世人都晓神仙好，只有金银忘不了。
终将只恨聚无多，及到多时眼闭了。
世人都晓神仙好，只有姣妻忘不了。
君生日日说恩情，君死又随人去了。
世人都晓神仙好，只有儿孙忘不了。
痴心父母古来多，孝顺儿孙谁见了。

Machine Translation:

People all know the goodness of divine beings, Yet they cannot forget the lure of fame and power. Where now are those ancient kings and ministers? Buried under wild graves, overgrown with grass.
People all know the goodness of divine beings, But they cannot abandon their pursuit of wealth. In the end, they regret amassing too much, For when they have plenty, their eyes close forever.
People all know the goodness of divine beings, But they cannot let go of their charming spouses. Day by day, they express love and affection, Yet, at death, they depart with others.
People all know the goodness of divine beings, But they cannot forget their children and grandchildren. Filial piety has long been cherished by parents, But who has seen children truly honor it?

Famous Translator David Hawkes' Translation:

Men all know that salvation should be won,
But with ambition won't have done, have done.
Where are the famous ones of days gone by?
In grassy graves they lie now, everyone.

Men all know that salvation should be won,
But with their riches won't have done, have done.
Each day they grumble they've not made enough.
When they're enough, it's goodnight everyone.

Men all know that salvation should be won,
But with their loving wives they won't have done.
The darlings every day protest their love;
But once you're dead, they're off with another one.

Men all know that salvation should be won,
But with their children won't have done, have done.
Yet though of parents fond there is no lack,
Of grateful children saw i never a one.

Analysis: The main idea of the source language is that "People seek divine status for joy but overlook fame and wealth's meaning. History proves no one achieves immortality—all enter graves.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 4: 1007-1025, 2024
DOI: 10.55214/25768484.v8i4.1478

Desire for riches ends futilely, and people can't take wealth beyond death. Divine life means abandoning worldly ties, but family rarely reciprocates parental care in old age." From the above two types of translated texts, it is evident that machine translation lacks depth, offering superficial understanding and overly lengthy renditions, which fails to capture the literary essence of *Dream of the Red Chamber*. Conversely, David Hawkes' translation precisely conveys the original meaning while adopting a literary style and form that align with the book.

In conclusion, adopting varied translation strategies for different text levels, considering the distinct purposes and quality requirements of translations, greatly maximizes translation efficiency.

3. Corpus Construction in Human-Machine Interaction Translation

Currently, machine translation systems have advanced into a stage where neural network translation systems dominate. With continuous breakthroughs in artificial intelligence technology, AI-based machine translation has become a pivotal research focus. Continuous research and learning in machine translation are crucial at present.

3.1. What Significance Does Corpus Construction Hold?

Over the past few decades, the most significant advancement in neural network-based machine translation has been "deep learning", a widely popular term today. However, within the realm of artificial intelligence, the core breakthrough in deep learning is not merely about algorithmic progress, but it resides in feature extraction. The essence of AI's competition lies in capturing features, which necessitates a foundation built upon massive data. To illustrate, consider a chef cooking, without quality ingredients, excellent dishes are unattainable. In the context of neural network machine translation in AI, corpus serve as the ingredients, computers as the cooking utensils, the process akin to the chef's cooking, and the final product as the executable translation program.

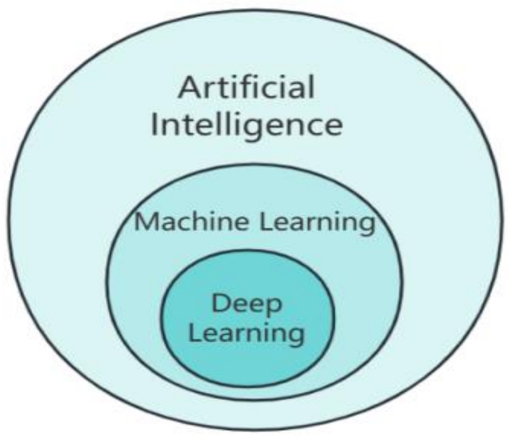

Figure 9.
The relationship between ai, machine learning, and deep learning.

Deep learning requires specific learning materials. For neural network-based translation machines, the material for deep learning is the corpus, signifying that corpus construction in the era of big data is a crucial foundation for artificial intelligence development. By considering the corpus as a knowledge base, computers learn various information from it. Alternatively, viewing the corpus as an infinite, continually generating text collection remains the primary approach in language automation processing under the umbrella of artificial intelligence for machine translation. Machine translation systems, based on neural networks' self-learning capabilities and enormous corpus capacities, constitute the core of language services.

ISSN: 2576-8484
Vol. 8, No. 4: 1007-1025, 2024
DOI: 10.55214/25768484.v8i4.1478

Though China has developed certain corpus, such as the Chinese-English Parallel Corpus and the Chinese Language Resources Consortium, differences exist between corpora in big data and traditional ones. Large data corpus present many distinct new features and sources. Therefore, under the context of artificial intelligence, constructing new big data corpora holds significant importance in novel language service models.

3.2. Where Does the Corpus Data Come from?

Various sources contribute to building corpus, especially in the context of big data, where any fragments of data accessible on the internet could potentially serve as sources for corpus data.

Enterprises Data. Enterprise data is a vital, dependable source within corpus collections. It originates from official documents and internal databases of specialized enterprises, ensuring high-quality content. However, due to privacy concerns, access to this valuable resource is limited. Still, corpus builders can gather keywords from official enterprise websites to craft professional, domain-specific corpus.

Internet Data. In the age of big data, the internet holds an immense volume of diverse and complex information. Constructing corpora from this data poses challenges due to its vastness and noise. Yet, refining these fragments into specialized corpora could significantly advance machine learning.

People Created Data. Amid the 5G era, people generate substantial corpus data through social platforms, like literary translation discussions on forums. Despite its volume and inherent noise, refining this data into corpora and using it to train translation systems could significantly advance machine translation, especially for high-level publication texts' translation.

Translation Memory (TM). Translation memory uses computer-assisted translation software to match and store sentence-level translations. It just like a repository where past translations are stored. When similar text is encountered, the system automatically compares it to the repository for translation.

Machine-generated Knowledge Graph Data. With the advent of big data, computers can amalgamate diverse data using methods such as data mining and knowledge fusion. This synthesis results in a unified knowledge repository and services like Knowledge Graphs. AI-integrated corpora feature graph structures, connecting extensive fragmented data through Knowledge Graphs to cater to immediate, dynamic, and fragmented micro-language needs.

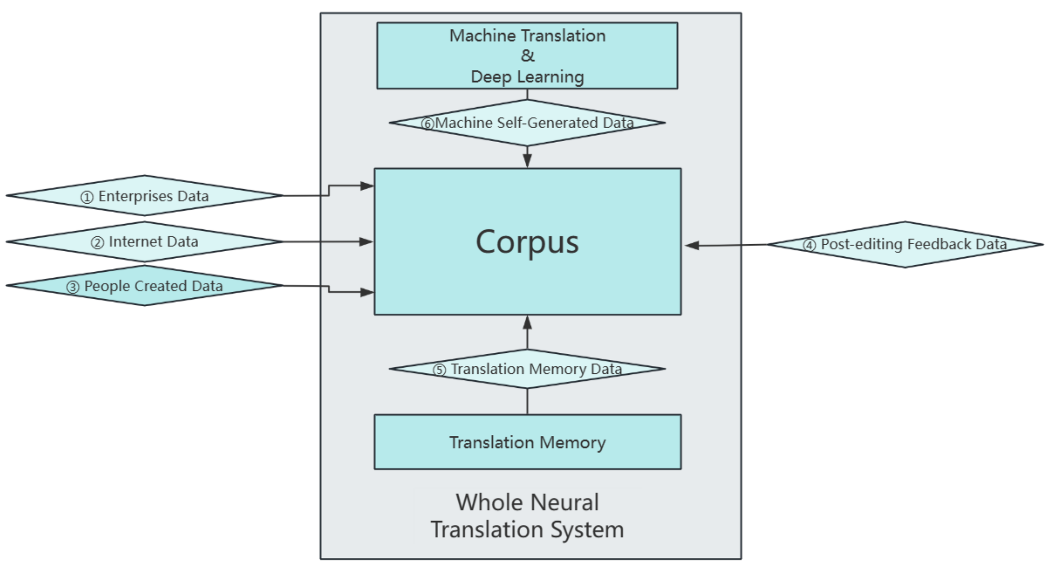

Figure 10.
Accessible corpus source chart.

ISSN: 2576-8484
Vol. 8, No. 4: 1007-1025, 2024
DOI: 10.55214/25768484.v8i4.1478

4. How Human and Machine Interact with Each Other?

4.1. Human and Machine Interaction Flowchart

Figure 11 provides the details of the assumption about this paper. Human beings are conscious creatures with autonomous thinking capabilities. When facing different types of texts, the human brain automatically processes information in hierarchical layers. For reference-level texts, machines can autonomously perform self-translation. However, for texts at the standard and publication levels, a preliminary manual editing process is initiated to enhance the text's comprehension by machines. Subsequently, the text is input into the translation system to obtain a machine-translated raw text. Following this, human intervention is employed to perform post-editing on the machine's initial translation, thereby achieving a rationalized quality in the target language text.

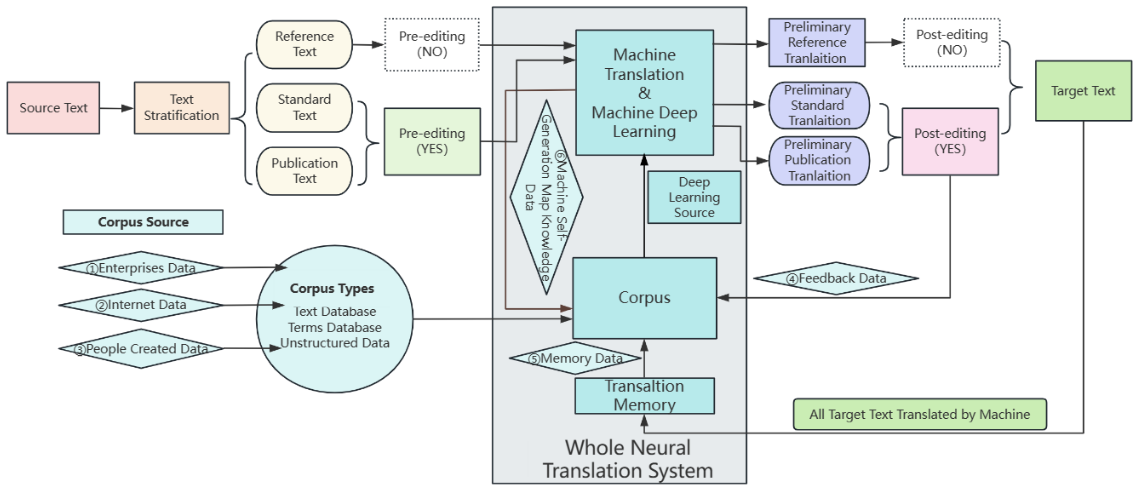

Figure 11.
The whole translation process in human-machine interaction translation.

Furthermore, the post-editing personnel can provide feedback on the modifications and editing made, which can be integrated into the translation system. Additionally, the final target text can also be fed back into the translation system to construct a translation memory. The machine translation system absorbs this feedback, and the system's programmers integrate the content into the corpus, providing the machine with richer and more reliable materials for deep learning. Consequently, the machine's thinking process becomes more akin to human cognition, thereby improving the quality of machine translation.

In the era of artificial intelligence, the interaction between humans and machines involves adopting translation strategies that are either human-centered or machine-centered, depending on the text's hierarchical levels. Coupled with continuous training of the machine and the construction of learning materials within the corpus, this approach maximizes translation efficiency and rationalizes translation quality in the context of human-machine interaction.

4.2. Machine's Roles

Machine translation serves as a powerful aide to human translation. It stands as a monumental achievement of artificial intelligence, leveraging robust algorithms and machine self-learning capabilities. The speed at which machine translation operates surpasses human capabilities, and its translation capacity outstrips the cognitive reach of the human mind. When handling the fragmented translations on a vast network scale, machines swiftly engage in deep learning of associated knowledge, constructing an extensive knowledge graph.

DOI: 10.55214/25768484.v8i4.1478

However, machine translation not only relies on the support of computers and mathematics but also necessitates the backing of numerous disciplines such as linguistics, psychology, neuroscience, sociology, anthropology, history, life sciences, and more. Only by continually amalgamating the knowledge from these diverse fields into an immense corpus can the research in machine translation progress further towards breaking through the bottleneck of "humanities hard-core." Consequently, machine translation can effectively complement human translation, compensating for deficiencies in human speed and capacity, thereby achieving the goal of saving time and labor costs.

4.3. Human's Roles

Human translation represents a sophisticated intellectual activity. Translation involves not only the transformation of linguistic structures but also encompasses daily life knowledge, societal understanding, historical insights, cultural context, mental processes related to human thought, cognitive ideas, thinking patterns, emotional desires, and more.

A translator naturally categorizes the text, a straightforward mental process inherent to the translator. Computers lack the concept of textual hierarchies. When text is inputted into a machine, it generates a translated output without the capacity to assess fidelity, appropriateness, and elegance in translation. Machines operate within the simplistic input-transform-output paradigm during translation. Hence, diverse strategies informed by human thought processes are necessary for handling specific texts.

For texts within reference-level, the scope is readily identifiable, requiring minimal human intervention as machines autonomously manage the translation process. The sophistication of human translation primarily manifests in the interactive translation modes between standard-level and publication-level texts. Pre-editing for standard texts reduces inherent errors, enhancing the quality of the text to be translated. Post-translation editing involves modifying and re-creating machine-generated translations to align more closely with the target text's expression.

Concerning publication-level texts, translating literary works essentially involves a recreation based on source material. This demands not only bilingual competence but also a profound literary background in the target language, emphasizing the necessity of human 'thought processes' in this creative endeavor.

5. Conclusion

This paper primarily discusses the impact of artificial intelligence and big data technologies on the language service industry, emphasizing the disparities between machine translation and human translation in terms of speed, capacity, and cost. Despite the numerous advantages of machine translation, its fully autonomous translation techniques are still immature, making it challenging to achieve high-quality translations without human intervention. Pre-editing and post-editing play a pivotal role in machine translation by rectifying translation errors and considering humanistic factors. Furthermore, with the globalization of economies and the increasing informatization, the diverse requirements for translation quality based on different texts across different industries necessitate various translation strategies. This article suggests that, given the backdrop of artificial intelligence and big data, employing different translation strategies based on text stratification and incorporating corpus construction in the era of big data can facilitate an optimized collaboration between human expertise and machine capabilities, ultimately maximizing translation efficiency.

With the continual advancement of artificial intelligence technology, the precision of machine translation has progressively enhanced, redefining the roles of humans and machines in translation and posing new demands on contemporary foreign language education. Particularly in translation education, synchronization with technological developments is essential to nurture translation professionals adaptable to the evolving landscape. This article proposes several recommendations in light of the current scenario. Firstly, integrating relevant technologies such as artificial intelligence, big data, and machine translation into the curriculum is crucial. Equipping students with an understanding and

DOI: 10.55214/25768484.v8i4.1478

mastery of these technologies' fundamental principles and applications facilitates an appreciation of the respective strengths and limitations of humans and machines, fostering an awareness among students of the collaborative trend between humans and machines in the future. Secondly, fostering students' interdisciplinary competencies spanning linguistics, computer science, and cultural studies aids in a more comprehensive comprehension and utilization of technology in translation endeavors, striving for maximized translation efficiency. Furthermore, emphasizing practical teaching methodologies encourages students to apply technology in authentic translation projects and experiment with collaborative translation with machines, enhancing their preparedness for real-world scenarios. Lastly, despite rapid technological advancements, humanistic literacy remains profoundly significant, especially in the translation of publication-level texts. Cultivating students' knowledge in literature, history, culture, and humanities enhances their capability to grasp translation contexts and backgrounds, serving as the cornerstone of their competence in any human-machine interaction.

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Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 4: 1007-1025, 2024
DOI: 10.55214/25768484.v8i4.1478