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A Comprehensive Review of Machine Learning Techniques for Multilingual and Cross-Lingual Interpretation

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Abstract

Multilingual interpretation — automatically understanding, translating, or transcribing across multiple languages and language varieties — has seen rapid advances due to transformer architectures, large multilingual pretrained models, and scalable datasets. While large multilingual language models (MLLMs) and end-to-end neural approaches greatly improved performance on major languages, persistent challenges remain: low-resource languages, code-switching, evaluation beyond n-gram overlap, cultural and pragmatic nuance, and model bias. This review summarizes core architectures and training strategies, commonly used datasets and benchmarks, evaluation approaches, practical applications, open challenges, and promising research directions.

Keywords

Multilingual, Machine Translation, Multilingual Language Models, Code-Switching, Speech Recognition, Evaluation Metrics, Low-Resource

1. Introduction

Multilingual interpretation refers to the set of computational tasks that enable machines to understand, process, and translate information across multiple human languages. These tasks play a critical role in reducing language barriers in an increasingly globalized and digitally connected world. Core multilingual interpretation tasks include machine translation (MT), which focuses on converting text or speech from one language to another; cross-lingual natural language understanding, such as multilingual text classification, sentiment analysis, and information retrieval; automatic speech recognition (ASR) across diverse languages; and spoken language translation (SLT), which integrates speech recognition and translation into a unified pipeline. Together, these tasks form the backbone of modern multilingual communication systems used in applications such as real-time translation, global information access, multilingual chatbots, and digital inclusion initiatives (Koehn, 2020).

Over the past decade, and particularly in the last five years, the field of multilingual interpretation has undergone a paradigm shift driven by advances in machine learning and deep neural networks. Earlier statistical and rule-based approaches relied heavily on handcrafted linguistic rules or parallel corpora tailored to specific language pairs, making them costly and difficult to scale. The introduction of deep learning, especially neural machine translation and neural sequence modeling, significantly improved translation fluency and robustness. This progress accelerated further with the adoption of transformer-based architectures, which replaced recurrent and convolutional models by leveraging self-attention mechanisms to capture long-range dependencies more efficiently (Vaswani et al., 2017). Transformers quickly became the dominant backbone for multilingual interpretation tasks due to their scalability and strong empirical performance.

A defining trend in recent multilingual systems is large-scale pretraining on multilingual corpora. Multilingual pretrained language models are trained on massive collections of text spanning dozens or even hundreds of languages using self-supervised objectives such as masked language modeling or sequence-to-sequence denoising. This approach allows models to learn shared semantic and syntactic representations across languages, enabling knowledge transfer from high-resource languages to low-resource ones. As a result, modern multilingual models often demonstrate strong zero-shot and few-shot learning capabilities, where they can perform tasks in languages that were not explicitly seen, or were only sparsely represented, during supervised fine-tuning (Devlin et al., 2019; Conneau et al., 2020).

In parallel with advances in text-based models, speech-centric multilingual interpretation has benefited from end-to-end neural architectures. Traditional speech translation pipelines treated ASR and MT as separate components, which led to error propagation and limited adaptability across languages. End-to-end speech models aim to directly map speech signals to text or translated output, reducing system complexity and allowing joint optimization. Multilingual and cross-lingual speech models further extend this idea

by sharing acoustic and linguistic representations across languages, improving performance for under-resourced languages and code-switching scenarios (Bérard et al., 2018). These developments have made real-time multilingual speech interpretation increasingly feasible in practical settings.

Despite these achievements, the effectiveness of multilingual interpretation systems remains strongly influenced by the composition and balance of pretraining data. High-resource languages such as English, Chinese, and major European languages dominate most large-scale datasets, which can lead to performance disparities when models are applied to low-resource or morphologically rich languages. In such cases, negative transfer or representational bias may occur, limiting the benefits of multilingual learning (Joshi et al., 2020). Furthermore, downstream task characteristics, including domain specificity, modality (text versus speech), and linguistic phenomena such as code-switching or dialectal variation, significantly affect model generalization.

In summary, multilingual interpretation has evolved into a central research area within machine learning, driven by transformer architectures, multilingual pretraining strategies, and end-to-end speech models. While these approaches have enabled remarkable zero-shot and few-shot cross-lingual transfer, they also introduce new challenges related to data imbalance, fairness, and task-specific adaptability. Understanding these foundations is essential for designing robust, inclusive, and scalable multilingual systems, and it provides the motivation for continued research into improved architectures, datasets, and evaluation methodologies in multilingual interpretation.

2. Architectures & Training Paradigms

Modern multilingual interpretation systems are largely built upon transformer-based neural architectures, which have redefined the way language representation and sequence modeling are approached in natural language processing. The encoder–decoder framework, originally popularized in neural machine translation, has become the dominant paradigm for machine translation (MT), spoken language translation (SLT), and other sequence-to-sequence tasks. In this architecture, the encoder processes an input sequence into contextualized representations, while the decoder generates the output sequence conditioned on those representations. The introduction of the transformer model replaced recurrent neural networks with self-attention mechanisms, enabling parallel computation and more effective modeling of long-range dependencies across tokens (Vaswani et al., 2017). This design significantly improved translation quality and computational efficiency, making it feasible to train large multilingual systems at scale.

The same attention-based foundations are shared by encoder-only and encoder–decoder multilingual language models. Encoder-only models such as multilingual BERT (mBERT) and XLM-RoBERTa (XLM-R) are typically trained using masked language modeling objectives, where portions of the input text are masked and the model learns to predict them based on contextual cues (Devlin et al., 2019; Conneau et al., 2020). This objective encourages the learning of deep bidirectional representations that capture syntactic and semantic regularities across languages. Encoder–decoder models such as mT5 extend this paradigm by employing sequence-to-sequence pretraining objectives, including denoising and text-to-text transformations, enabling them to handle a broader range of tasks such as translation, summarization, and cross-lingual question answering (Xue et al., 2021). Additionally, translation language modeling objectives explicitly align parallel sentences from different languages, strengthening cross-lingual representation sharing. These shared architectural principles allow multilingual models to transfer knowledge across languages and tasks, facilitating zero-shot and few-shot learning scenarios where labeled data is scarce.

Building on these foundations, multilingual large language models (MLLMs) have emerged as a natural extension of large-scale pretraining strategies. MLLMs are trained on massive multilingual corpora containing dozens or even hundreds of languages, often using subword tokenization techniques such as SentencePiece to construct a shared vocabulary across languages. This shared vocabulary enables parameter sharing and cross-lingual alignment at the lexical and subword levels. During fine-tuning, these pretrained models are adapted to downstream tasks including translation, classification, retrieval, and dialogue generation. However, designing effective alignment strategies remains a central challenge. Approaches such as language-specific adapters and task-specific adapters introduce lightweight modules into a shared backbone, allowing models to preserve common multilingual knowledge while specializing for individual languages or tasks (Pfeiffer et al., 2020). These modular strategies help mitigate catastrophic interference, where training on one language may degrade performance on another.

Despite the impressive capabilities of MLLMs, the distribution of training data plays a decisive role in shaping model performance. High-resource languages dominate web-scale corpora, leading to imbalanced representation learning. As a result, models often achieve superior performance in languages with abundant data while underperforming in low-resource languages, especially those with complex morphology or non-Latin scripts. Empirical studies have shown that linguistic diversity remains unevenly supported, and performance gaps persist even in massively multilingual settings (Joshi et al., 2020). Addressing this imbalance requires strategies such as data augmentation, balanced sampling, and typology-aware training techniques to ensure more equitable cross-lingual transfer.

In parallel with text-based multilingual models, end-to-end speech models have gained significant prominence in multilingual interpretation. Traditional speech translation pipelines treated automatic speech recognition (ASR) and machine translation as separate components, which introduced cascading errors and limited optimization across stages. End-to-end approaches instead employ a unified neural architecture that directly maps speech signals to text transcripts or translated outputs, typically using transformer-based encoders capable of modeling acoustic and linguistic patterns simultaneously (Bérard et al., 2018). Multilingual ASR models share acoustic representations across languages, improving generalization and enabling better handling of code-switching scenarios where speakers alternate between languages within a single utterance.

More recently, multimodal approaches have extended this paradigm by jointly modeling speech and text within a shared representation space. These models leverage cross-modal transfer, where knowledge learned from large text corpora enhances speech processing performance, and vice versa. Such integration is particularly valuable in low-resource scenarios, where speech data may be limited but textual resources are comparatively richer. By aligning representations across modalities, multimodal models can improve robustness, enhance translation quality, and support more inclusive multilingual systems. Collectively, these architectural

and training paradigms demonstrate how shared transformer backbones, large-scale multilingual pretraining, and multimodal integration have become central to advancing machine learning for multilingual interpretation.

3. Datasets & Benchmarks

Datasets and benchmarks play a foundational role in the development, training, and evaluation of multilingual interpretation systems, as they directly influence model generalization, fairness, and cross-lingual transfer capabilities. In text-based multilingual interpretation, parallel corpora have traditionally served as the backbone for supervised machine translation and cross-lingual learning. Well-known resources such as the Workshop on Machine Translation (WMT) datasets, Europarl, and OPUS provide aligned sentence pairs across multiple language pairs and domains. These datasets have been instrumental in advancing neural machine translation by enabling supervised training and standardized comparison across models. However, they are often biased toward European and high-resource languages, reflecting geopolitical and economic factors rather than true global linguistic diversity (Koehn, 2020).

With the rise of large-scale multilingual pretraining, massive crawled corpora have become increasingly important. These corpora are typically collected from web sources and contain raw or weakly filtered text in dozens or hundreds of languages. Such datasets underpin multilingual large language models (MLLMs) and allow self-supervised learning objectives, such as masked language modeling or denoising, to be applied at scale. The advantage of these corpora lies in their size and linguistic breadth, which enable models to learn shared representations across languages without requiring explicit parallel alignment. However, web-crawled data also introduces challenges, including noise, domain imbalance, uneven language representation, and the propagation of societal and cultural biases present in online content (Conneau et al., 2020). As a result, while these corpora support impressive zero-shot and few-shot transfer, they may still inadequately represent low-resource and under-documented languages.

In the speech domain, multilingual interpretation has benefited from the emergence of large open speech datasets. Mozilla Common Voice is a prominent example, offering crowdsourced speech recordings with transcriptions across a wide range of languages and accents. Its open and community-driven nature has helped expand coverage to languages that were previously underrepresented in speech research. Other datasets such as MuST-C and CoVoST focus on spoken language translation, providing aligned speech–text or speech–translation pairs that enable end-to-end speech translation research (Di Gangi et al., 2019). These datasets have been critical in推动 the shift from traditional pipeline-based systems to unified end-to-end speech models. Nevertheless, speech datasets often vary significantly in recording quality, speaker demographics, and domain consistency, which can affect model robustness and comparability.

Beyond monolingual and parallel datasets, specially curated code-switching datasets address an increasingly important aspect of real-world multilingual communication. Code-switching, where speakers alternate between languages within a single utterance or conversation, is common in multilingual societies but remains underrepresented in standard benchmarks. Existing code-switching datasets are typically limited in size and scope, focusing on specific language pairs or domains, which restricts their general applicability. This scarcity makes it difficult to train and evaluate models that can robustly handle mixed-language input, especially in speech recognition and spoken language translation tasks (Joshi et al., 2020).

To enable systematic evaluation, several multilingual benchmarks have been proposed. Shared tasks and benchmarks such as WMT provide standardized test sets and evaluation protocols for machine translation, fostering reproducibility and fair comparison. FLORES extends this idea by offering a carefully curated benchmark covering a wider range of languages, including some low-resource ones, with a strong emphasis on evaluation quality. Similarly, multilingual GLUE and XGLUE benchmarks adapt popular natural language understanding tasks to a multilingual setting, allowing researchers to assess cross-lingual transfer and generalization across diverse tasks and languages (Hu et al., 2020). Despite these advances, benchmark coverage remains uneven. Truly low-resource languages, dialectal variation, and code-switching phenomena are still sparsely represented, limiting the ecological validity of current evaluations.

Overall, while existing datasets and benchmarks have significantly advanced multilingual interpretation research, they also expose critical gaps. The dominance of high-resource languages, limited representation of speech diversity, and inadequate coverage of code-switching highlight the need for more inclusive data collection and evaluation strategies. Addressing these limitations is essential for building multilingual systems that are not only accurate but also equitable and representative of real-world language use.

4. Evaluation Metrics

Evaluation metrics are central to the development and comparison of multilingual interpretation systems, as they provide quantitative signals for model optimization and benchmarking. In machine translation and related cross-lingual tasks, automatic metrics have traditionally been used due to their speed, reproducibility, and cost-effectiveness. Among these, BLEU (Bilingual Evaluation Understudy) has long served as the standard metric for evaluating translation quality. BLEU measures n-gram overlap between a system-generated translation and one or more human reference translations, applying a brevity penalty to discourage overly short outputs (Papineni et al., 2002). Its simplicity and language-agnostic design contributed to its widespread adoption in shared tasks such as WMT. Similarly, chrF, a character n-gram F-score metric, was introduced to better handle morphologically rich languages by evaluating character-level overlap rather than relying solely on word-level matching (Popović, 2015). ChrF has shown improved sensitivity to inflectional variation and spelling differences, making it particularly useful for languages with complex morphology.

Despite their popularity, traditional lexical overlap metrics such as BLEU and chrF have well-documented limitations. First, they rely heavily on surface-form similarity and may fail to capture semantic adequacy or contextual meaning when valid paraphrases differ lexically from reference translations. This issue becomes more pronounced in morphologically rich or low-resource languages, where multiple valid forms may exist for the same meaning. Second, these metrics often struggle with free word order languages, where syntactic flexibility can reduce n-gram overlap without necessarily degrading translation quality. Third, lexical metrics are

sensitive to the number and diversity of reference translations; when only a single reference is available, the metric may unfairly penalize legitimate alternative renderings (Callison-Burch et al., 2006). Consequently, while BLEU remains a useful comparative tool, it does not always correlate strongly with human judgments at the sentence level, especially in multilingual and low-resource contexts.

To address these shortcomings, learned evaluation metrics based on neural networks have gained prominence. Metrics such as COMET employ pretrained multilingual language models to evaluate translations by modeling semantic similarity and contextual adequacy between source, reference, and candidate outputs (Rei et al., 2020). By leveraging cross-lingual representations, COMET and related neural evaluators can capture deeper semantic relationships beyond surface-level overlap, often achieving higher correlation with human assessments in shared evaluation campaigns. These metrics can be trained using human-annotated quality scores, enabling them to approximate human judgment patterns more closely than traditional lexical metrics. As multilingual pretrained models improve, neural metrics have correspondingly advanced in their ability to assess adequacy, fluency, and even discourse-level coherence.

However, learned metrics are not without challenges. Because they rely on supervised training with annotated datasets, their performance depends heavily on the quality and diversity of the underlying training data. If human evaluation datasets are biased toward specific domains, language pairs, or stylistic conventions, the learned metric may inherit these biases and generalize poorly to other contexts. Furthermore, neural metrics require careful calibration to avoid overestimating certain stylistic patterns or penalizing dialectal and low-resource language varieties. Computational cost is another concern, as neural evaluation metrics are more resource-intensive than lexical overlap measures. These considerations highlight the importance of transparency and validation when deploying learned metrics in real-world evaluation pipelines.

Recent research increasingly advocates for a hybrid evaluation strategy that combines lexical metrics, neural metrics, and human assessment. Lexical metrics remain valuable for reproducibility and rapid benchmarking, while neural metrics offer improved semantic sensitivity. For high-stakes applications such as legal, medical, or governmental translation, human evaluation remains indispensable to assess pragmatic nuance, cultural appropriateness, and factual accuracy (Freitag et al., 2021). Integrating human-in-the-loop evaluation frameworks and developing task-specific benchmarks are therefore considered essential steps toward more reliable multilingual system assessment. Overall, evaluation metrics in multilingual interpretation are evolving from purely surface-based measures to more holistic, semantically informed frameworks that aim to better reflect real-world translation quality.

5. Key Challenges

Multilingual interpretation systems, despite their rapid advancement, continue to face significant structural and linguistic challenges that limit their inclusiveness and real-world robustness. One of the most persistent issues is data imbalance across languages. Multilingual large language models (MLLMs) are typically trained on web-scale corpora, where a small number of high-resource languages—such as English, Chinese, Spanish, and French—dominate the available data. Consequently, these languages benefit disproportionately from model capacity, while low-resource and under-documented languages receive limited representation in training data (Joshi et al., 2020). This imbalance leads to weaker cross-lingual transfer, reduced translation quality, and poorer downstream task performance for low-resource languages. Even though multilingual pretraining aims to share representations across languages, transfer is not uniformly effective, particularly for typologically distant languages. To mitigate this issue, researchers have explored massively multilingual pretraining with more balanced sampling strategies, data augmentation techniques such as back-translation, unsupervised machine translation using monolingual corpora, and parameter-efficient transfer methods like language-specific adapters (Conneau et al., 2020; Pfeiffer et al., 2020). While these strategies improve representation learning for under-resourced languages, the performance gap remains substantial in many cases.

Another critical challenge concerns evaluation gaps in multilingual systems. Automatic metrics such as BLEU and chrF provide convenient and reproducible benchmarks but can be misleading, particularly for low-resource languages and creative or domain-specific translations. These metrics often prioritize surface-form similarity rather than semantic adequacy or pragmatic correctness. As a result, systems optimized for lexical overlap may produce outputs that score well numerically but fail to meet real communicative needs. Neural evaluation metrics, while more semantically informed, also depend on training data distributions and may not generalize across domains or linguistic varieties (Rei et al., 2020). For high-stakes contexts such as healthcare, law, and diplomacy, reliance solely on automated metrics is insufficient. Human evaluation remains essential for assessing nuance, contextual appropriateness, tone, and factual accuracy (Freitag et al., 2021). The challenge lies in balancing scalability with reliability, as large-scale human evaluation is expensive and time-consuming.

Closely related to evaluation is the broader issue of cultural and pragmatic nuance. Language is deeply embedded in culture, social norms, and contextual expectations. Literal translation approaches often fail to capture idiomatic expressions, humor, politeness strategies, or culturally specific references. For example, metaphors and proverbs may require adaptation rather than direct translation to preserve meaning. While transformer-based models excel at statistical pattern recognition, they typically lack explicit modeling of pragmatics and discourse-level reasoning. This limitation can result in translations that are grammatically correct but culturally inappropriate or pragmatically awkward. Consequently, in professional domains such as publishing, media localization, and international communication, human post-editing remains necessary to ensure quality and cultural fidelity (Koehn, 2020). Developing models that integrate pragmatic reasoning or sociolinguistic awareness remains an open research direction.

Bias and fairness represent another major concern in multilingual interpretation. Large-scale pretraining corpora harvested from the internet inevitably reflect existing societal inequalities and stereotypes. Gender bias, geopolitical bias, and representation bias can be encoded in multilingual embeddings and propagate into translation or classification outputs. In multilingual contexts, bias detection becomes more complex because stereotypes and sensitive attributes may manifest differently across cultures and languages (Bender et al., 2021). Moreover, mitigation strategies effective in one language may not generalize to others. Ensuring equitable performance across linguistic communities requires not only balanced data collection but also bias-aware training objectives and cross-cultural validation frameworks.

Finally, code-switching and orthographic variation present practical challenges in real-world multilingual environments. In many multilingual societies, speakers naturally alternate between languages within a single utterance, and written forms may include inconsistent spelling, transliteration, or informal adaptations. Standard multilingual models trained on clean, monolingual corpora often struggle with such mixed-language input. In speech recognition, code-switching complicates acoustic modeling and language identification, while in text translation it disrupts tokenization and contextual alignment (Joshi et al., 2020). Synthetic data augmentation techniques and multilingual language model fusion have shown promise in addressing these issues, yet they remain incomplete solutions. Robust handling of code-switching requires more representative datasets and models explicitly designed to capture dynamic language mixing patterns.

Overall, these challenges highlight that multilingual interpretation is not merely a technical scaling problem but a complex sociolinguistic and ethical endeavor. Addressing data imbalance, improving evaluation frameworks, incorporating cultural nuance, mitigating bias, and modeling real-world language variation are essential steps toward building inclusive and trustworthy multilingual systems.

Machine learning has fundamentally transformed multilingual interpretation, enabling systems that can process, translate, and understand dozens or even hundreds of languages within unified frameworks. The shift from rule-based and statistical approaches to neural architectures—particularly transformer-based models—has allowed for scalable representation learning and powerful cross-lingual transfer. Through large-scale multilingual pretraining, models can now leverage shared linguistic structures across languages, achieving strong zero-shot and few-shot performance in tasks such as machine translation, cross-lingual classification, automatic speech recognition, and spoken language translation (Vaswani et al., 2017; Conneau et al., 2020). These developments have significantly reduced barriers to global communication and expanded access to information for multilingual communities.

However, the progress of multilingual interpretation systems must be evaluated alongside persistent structural and ethical challenges. Data imbalance remains a central limitation, as high-resource languages dominate training corpora, leading to uneven performance across linguistic communities (Joshi et al., 2020). While strategies such as massively multilingual pretraining, adapter-based transfer learning, and unsupervised approaches have narrowed performance gaps, true inclusivity requires sustained investment in data collection and representation for low-resource and endangered languages. Without such efforts, technological advancement risks reinforcing existing global inequalities in language access.

Evaluation practices also continue to evolve. Traditional lexical metrics such as BLEU provide standardized and reproducible benchmarks, but they often fail to capture semantic adequacy and pragmatic nuance. Neural metrics such as COMET offer improved correlation with human judgments, yet they are themselves shaped by the data on which they are trained (Rei et al., 2020). Consequently, high-stakes multilingual applications—particularly in legal, medical, and governmental contexts—still require human oversight. Future research must focus on more holistic evaluation frameworks that integrate lexical, neural, and human-centered assessments to better reflect communicative effectiveness and cultural fidelity.

Beyond technical performance, multilingual systems must address deeper linguistic and sociocultural dimensions. Cultural nuance, idiomatic expression, register, and discourse-level reasoning remain difficult for current models, which primarily learn statistical patterns from large corpora rather than explicit pragmatic rules (Koehn, 2020). Moreover, biases embedded in pretraining data can propagate across languages, creating fairness concerns that are amplified in multilingual settings. Ensuring equitable model behavior requires cross-cultural validation, bias mitigation strategies, and responsible dataset curation.

Emerging directions such as multimodal learning, cross-modal transfer between speech and text, and parameter-efficient adaptation methods provide promising avenues for further advancement. Integrating speech, text, and contextual signals may enhance performance in low-resource and code-switching scenarios, while modular architectures can support more flexible and scalable multilingual systems. At the same time, interdisciplinary collaboration between machine learning researchers, linguists, sociologists, and native speaker communities will be essential to ensure that technological progress aligns with real-world linguistic diversity.

In conclusion, machine learning for multilingual interpretation has achieved remarkable technical milestones, yet its future success depends not only on scaling models and data but also on addressing representation, evaluation, fairness, and cultural sensitivity. Building truly inclusive multilingual systems requires a balanced approach that combines architectural innovation with ethical responsibility and linguistic awareness.

6. Conclusion

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References

1. Bender, E. M., Gebru, T., McMillan-Major, A. and Shmitchell, S. (2021) 'On the dangers of stochastic parrots: Can language models be too big?', *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (FAccT)*, pp. 610–623.
2. Bérard, A., Besacier, L., Kocabiyikoglu, A. and Pietquin, O. (2018) 'End-to-end automatic speech translation of audiobooks', *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 6224–6228.
3. Callison-Burch, C., Osborne, M. and Koehn, P. (2006) 'Re-evaluating the role of BLEU in machine translation research', *Proceedings of the 11th Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, pp. 249–256.
4. Conneau, A., Khandelwal, K., Goyal, N., Chaudhary, V., Wenzek, G., Guzmán, F., Grave, E., Ott, M., Zettlemoyer, L. and Stoyanov, V. (2020) 'Unsupervised cross-lingual representation learning at scale', *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (ACL)*, pp. 8440–8451.
5. Devlin, J., Chang, M.-W., Lee, K. and Toutanova, K. (2019) 'BERT: Pre-training of deep bidirectional transformers for language understanding', *Proceedings of NAACL-HLT 2019*, pp. 4171–4186.
6. Di Gangi, M. A., Cattoni, R., Bentivogli, L., Negri, M. and Turchi, M. (2019) 'MuST-C: A multilingual speech translation corpus', *Proceedings of NAACL-HLT 2019*, pp. 2012–2017.
7. Freitag, M., Foster, G., Grangier, D., Ratnakar, V., Tan, Q., Turchi, M. and Macherey, W. (2021) 'Experts, errors, and context: A large-scale study of human evaluation for machine translation', *Transactions of the Association for Computational Linguistics*, 9, pp. 1460–1474.
8. Hu, J., Ruder, S., Siddhant, A., Neubig, G., Firat, O. and Johnson, M. (2020) 'XTREME: A massively multilingual multitask benchmark for evaluating cross-lingual generalization', *Proceedings of the 37th International Conference on Machine Learning (ICML)*, pp. 4411–4421.
9. Joshi, P., Santy, S., Budhiraja, A., Bali, K. and Choudhury, M. (2020) 'The state and fate of linguistic diversity and inclusion in the NLP world', *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (ACL)*, pp. 6282–6293.
10. Koehn, P. (2020) *Neural Machine Translation*. Cambridge: Cambridge University Press.
11. Papineni, K., Roukos, S., Ward, T. and Zhu, W.-J. (2002) 'BLEU: A method for automatic evaluation of machine translation', *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL)*, pp. 311–318.
12. Pfeiffer, J., Kamath, A., Rücklé, A., Cho, K. and Gurevych, I. (2020) 'AdapterFusion: Non-destructive task composition for transfer learning', *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, pp. 487–503.
13. Popović, M. (2015) 'chrF: Character n-gram F-score for automatic MT evaluation', *Proceedings of the Tenth Workshop on Statistical Machine Translation (WMT)*, pp. 392–395.
14. Rei, R., Stewart, C., Farinha, A. C. and Lavie, A. (2020) 'COMET: A neural framework for MT evaluation', *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 2685–2702.
15. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł. and Polosukhin, I. (2017) 'Attention is all you need', *Advances in Neural Information Processing Systems*, 30, pp. 5998–6008.
16. Xue, L., Constant, N., Roberts, A., Kale, M., Al-Rfou, R., Siddhant, A., Barua, A. and Raffel, C. (2021) 'mT5: A massively multilingual pre-trained text-to-text transformer', *Proceedings of NAACL-HLT 2021*, pp. 483–498.