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Understanding Knowledge Representation Concepts in Machine Translation: A Review

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ABSTRACT
Machine Translation is one of the core fields in Natural Language Processing and sub-branches in Artificial Intelligence, refers to a software that translates text or voice from one natural language into another natural language without human intervention. The major problem related to machine translation system is separating the translation algorithm from the grammatical rules due to the language complexity. As one of the solutions, the concept named knowledge representation can be used to address this problem. The aim of this paper is to deeply study the machine translation along with knowledge representation concept to understand the relationship between them that can be used to design accurate, well-performed machine translation systems. Therefore, the paper has focused on some interesting directions such as tasks of NLP, the process of machine translation, topology of latest machine translation approaches with their architectures and knowledge representation techniques. Moreover, the paper has reviewed twenty famous machine translations systems available in the world and captured their respective machine translation approach and knowledge representation technique. As the result of this study, it has been identified that most modern machine translation systems have used the concepts of machine learning due to some reasons such as data-driven learning, contextual understanding, scalability, continuous improvement and etc. Finally, the paper presented future directions of machine translation along with knowledge representation.

General Terms
Artificial Intelligence, Natural Language Processing.

Keywords
Machine Translation, Knowledge Representation

1. INTRODUCTION
Natural Language Processing (NLP) can be identified as one of the tracts of Artificial Intelligence, Linguistics and Computer Science concerned with making the computers more familiar with understanding statements or words written in natural languages [1]. The main aim of the NLP is to minimize the gap between computer's understanding and human languages [2]. At present, many systems are mixed with NLP concepts to make the system more robust, automated, and to meet future needs. Mainly, NLP has different tasks that can be further classified into multiple number of application areas. A detail classification of NLP tasks has been shown in Figure 1.

Machine translation (MT) is one of the core fields in natural language processing (NLP) and a sub-field of computational linguistics that uses computer software to translate text or speech from one language to another language with or without human intervention. This area has been aroused due to the drawbacks of human translation and to achieve the translation with reduced cost and time, increase speed and throughput [3] [4] [5]. Besides, machine translation has a great history since 1940s. At present, many machine translation systems have been developed to translate different languages in the world following different machine translation approaches. The basic architecture of the machine translation system contains three main components such as a dictionary (lexicon), grammar rules, and the translation program or algorithm. Accordingly, the major problem in machine translation systems is how to separate the translation algorithm from the grammatical rules as these rules will be different from one language to another language [6]. Meanwhile, a novel machine translation system has been emerged based on the concept named "knowledge representation" in 1980s and since then, the concept of knowledge representation became a main concept that is closely linked with machine translation.

Knowledge Representation and reasoning (KRR, KR&R, KR2) can be defined as one of the central fields in Artificial Intelligence (AI) [7]. Mainly it is used to represent real-world information in a model that the computer can understand and utilize to solve real-world problems. The main objective of knowledge representation in NLP is to enable machines to understand human natural languages [8]. Whilst many application areas in NLP such as machine translation, sentiment analysis, chatbots and virtual assistants, text summarization, and speech processing use knowledge representation to store, represent and model knowledge in natural languages in the world.

This paper presents a broad discussion about machine translation. In there, the process of machine translation and latest classification of machine translation approaches with their architectures are explained. Moreover, all these machine translation approaches have been compared according to BLEU score metrics to evaluate their performance. After that, the paper moves to the concepts named "Knowledge" and "Knowledge Representation" as knowledge representation is closely related and bonded with machine translation. In there, various knowledge representation techniques are explored and reviewed to highlight the importance and use of these techniques in machine translation. As the next chapter, some of the famous machine translation systems in the world have been studied to explore their machine translation approach and knowledge representation technique. Finally, the paper presents some predictions about the future directions of the machine translation along with knowledge representation considering all these findings. The advantage of this paper is that researchers and readers can clearly understand the latest facts in machine translation, and knowledge representation techniques with their future directions.

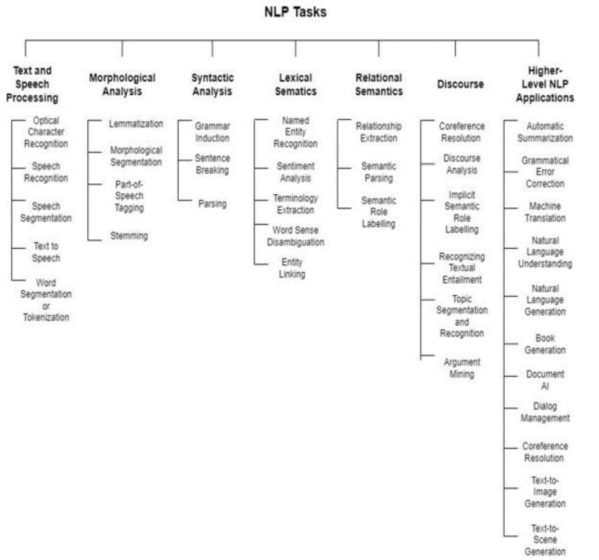

Fig 1: Classification of NLP Tasks

2. PROCESS OF MACHINE TRANSLATION

The process of machine translation starts with the input source language text that will be secondly deformed as the entered input text may contain figures, tables, flowcharts and etc. Then, this output will be entered into the pre-editing process to segment long sentences into short sentences. Also, the symbols such as punctuation marks that are not required for the translation process will be removed. As the next step, the text will be analyzed morphologically, syntactically, semantically and generates the internal representation of the input text to generate the internal representation of the target language. From this phase onwards, the process starts the generation process where morphological generation, syntactic generation, and semantic generation take place. After that, the text will be post-edited to ensure that the translation is up to the mark and reformatting is done to see non-translation portion in the generated text. Finally, as the output, the target language text will be provided [9]. Figure 2. shows the process of machine translation.

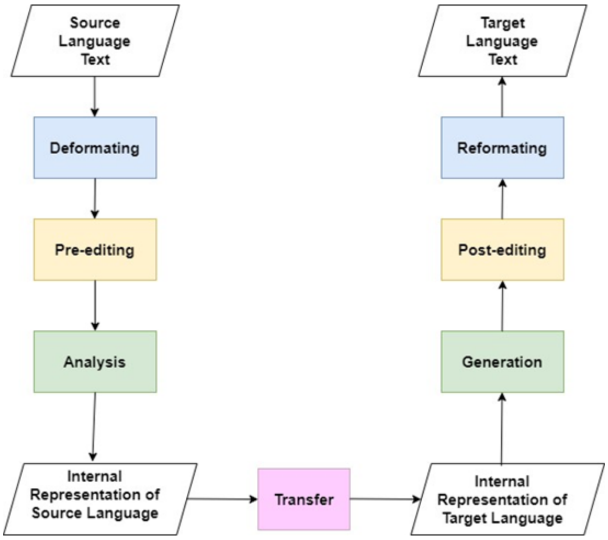

Fig 2: Process of Machine Translation

The analysis and generation phases of the machine translation process can be clearly identified using the machine translation pyramid that is shown in Figure 3.

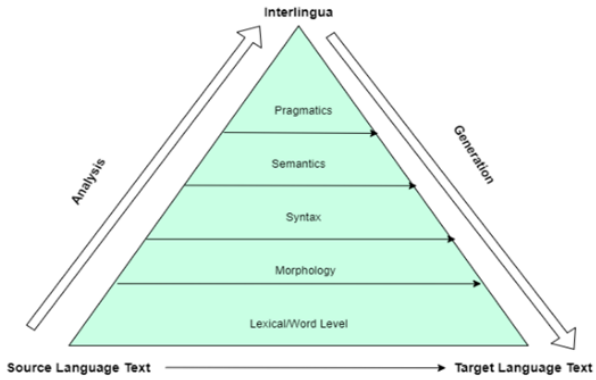

Fig 3: Machine Translation Pyramid

The aim behind developing automated machine translation systems in the world is the language barrier. However, the translation process is a challenging task due to the complexity of structural and stylistic differences between these languages such as word order, word sense and pronoun resolution. As a result, many researchers developed number of machine translation systems using different machine translation approaches.

3. MACHINE TRANSLATION APPROACHES

Machine translation systems can be broadly classified according to the methodology, knowledge type, representation, and interpretation. Under these facts, seven approaches can be identified such as dictionary-based, human-assisted, rule-based, corpus-based, hybrid, agent-based, and neural. Figure 4. shows the broad classification of machine translation approaches.

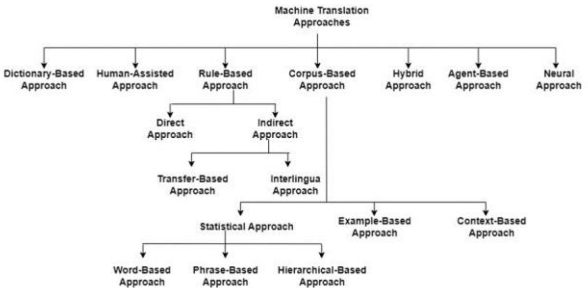

Fig 4: Classification of Machine Translation Approaches

3.1 Dictionary-Based Machine Translation Approach

This is one of the oldest machine translation approaches that was mainly used in cross-language retrieval systems. As the name implies, this method is based on language dictionaries that map individual words in the source language text to generate the equivalent target language text and perform word-to-word translation [10]. Therefore, the number of words in the source language text is a key fact in this approach. This method is not successful due to the different grammatical structures of languages and doesn't generate the exact correct meaningful output. Figure 5. shows the basic architecture of dictionary-based machine translation approach.

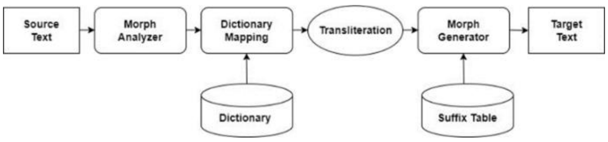

Fig 5: Dictionary-Based Machine Translation Approach

3.2 Human-Assisted Machine Translation Approach

This is also known as human-aided machine translation and abbreviated as HAMT. It is a special type of machine translation approach that combines machine translation with human expertise to improve the quality of the translation. In there, the computer system does most of the translation while acquiring human involvement for the tasks such as pre-editing, post-editing or other intermediate editing stages. This approach has been widely used to develop some famous machine translation systems in Indian region such as Anusaaraka, ManTra, MaTra, and Angalabarathi.

3.3 Rule-Based Machine Translation Approach

This was first introduced in the early period in machine translation, approximately in the 1940's. The approach contains a collection of grammar rules, lexicon that can be bilingual or multilingual and software programs to process the rules. Furthermore, the grammar rules include morphological, syntactic, and semantic rules, part of speech tagging and orthographic features to analyze the source language text and to generate the target language text. Moreover, it uses linguistic rules in three different stages such as in analysis, transfer and generation. Whilst the mechanism of the rule-based approach can be clearly identified using the machine translation pyramid. Furthermore, the rule-based approach can be classified as a direct approach, transfer-based approach and interlingua approach [11] [12].

3.3.1 Direct Approach

This approach starts from the bottom level of the machine translation pyramid. Also, it is the oldest and least popular approach that is also known as word-based translation or literal translation. It does a direct word level translation, and the bilingual dictionary is the major resource in this approach. Figure 6. shows the basic architecture of direct translation.

Fig 6: Direct Approach

3.3.2 Transfer-Based Approach

This approach uses three major components as analysis, transfer, and synthesis to produce the target language text while generating two intermediate representations related with source language and target language. At first, the source language text is analyzed morphologically, syntactically, and semantically and transformed into a less language specific intermediate structure related to source language. In the transfer stage, this generated intermediate structure will be transformed into a target language intermediate structure and synthesize the target language text as the output. Furthermore, it uses grammar rules and bilingual dictionaries to achieve this process. Figure 7. shows the basic architecture of transfer-based approach.

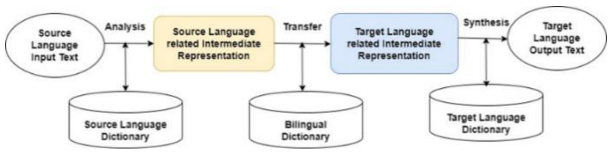

Fig 7: Transfer-Based Approach

3.3.3 Interlingua Approach

The word "Interlingua" is a combination of two Latin words "Inter" and "Lingua" stands for intermediate and language respectively. This approach is very similar to the transfer-based approach as this approach also generates an intermediate representation. The major difference between them is that in interlingua approach, the intermediate representation is independent of the languages while in transfer approach the intermediate representation is dependent upon the languages. Accordingly, the source language input will be transformed into a universal, independent intermediate representation in which the target language output will be generated. Figure. shows the basic architecture of interlingua approach.

Fig 8: Interlingua Approach

3.4 Corpus-Based Machine Translation Approach

This approach is also known as a data driven machine translation approach that is an alternative approach to machine translation to overcome drawbacks of the knowledge gathering issue appeared in the rule-based machine translation approach. This approach uses a bilingual parallel corpus consisting of massive amounts of raw data such as text and their translations to gather knowledge for new translations. Moreover, this approach can be classified as a statistical approach, example-based approach, and context-based approach.

3.4.1 Statistical Machine Translation Approach

In 1949, Warren Weaver introduced the idea of this machine translation approach. Statistical approach uses parallel aligned corpus and treats the translation process as a mathematical reasoning problem. Accordingly, every target language output is a translation with probability from the input source language. Generally, this approach is comprised of three modules such as language model, translation model and decoder model. Language model is used to calculate the probability of the target language ‘p(t)’ while the translation model is used to calculate the conditional probability of target language ‘p(t|s)’. Finally, the decoder model gives the best possible translation (t) by maximizing the two probabilities. Moreover, the statistical approach can be sub-divided as word-based SMT, phrase based SMT and Hierarchical phrases-based SMT. Figure 9. shows the architecture of the statistical machine translation approach.

$$t = \text{argmax } p(t|s) * p(t)$$

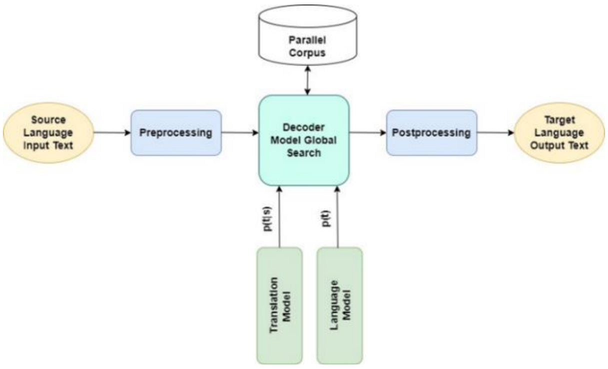

Fig 9: Statistical Machine Translation Approach

3.4.2 Example-Based Machine Translation Approach

Example-based machine translation approach or EBMT was first introduced in 1981 by Makoto Nagao. This is also known as memory-based translation approach as it was based on “Translation by Analogy” concept. Basically, the approach contains a set of source language sentences and their corresponding target language sentences with point-to-point mapping as examples. Accordingly, these given examples serve as knowledge to the system and used to translate similar new source language sentences into target language. Moreover, the architecture has parallel-aligned three machine-readable corpus and uses three stages such as matching, adaptation and recombination to achieve a better translation. Fig. 10. shows the architecture of example-based machine translation approach.

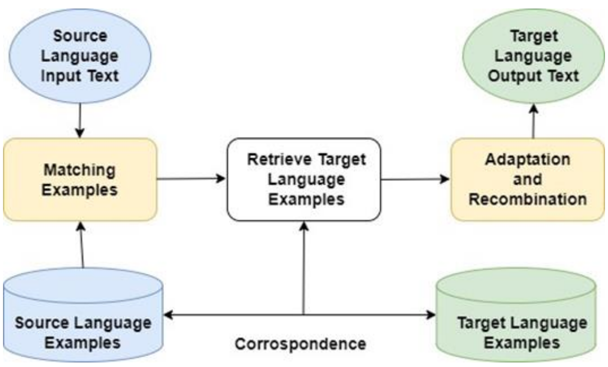

Fig 10: Example-Based Machine Translation Approach

3.4.3 Context-Based Machine Translation Approach

Context based machine translation approach or CBMT is a new paradigm for the corpus-based translation approach that was proposed in 2006. This can be identified as a phrase-based machine translation approach and different from other phrase-based translation approaches as CBMT works with contextual occurrence of the phrases while others rely on statistical occurrence of the phrases. Mainly, this approach provides a light-weight translation with the involvement of bilingual dictionary, flooder, synonym finder and n-grams [13]. Fig. 11. shows the architecture of context-based machine translation approach.

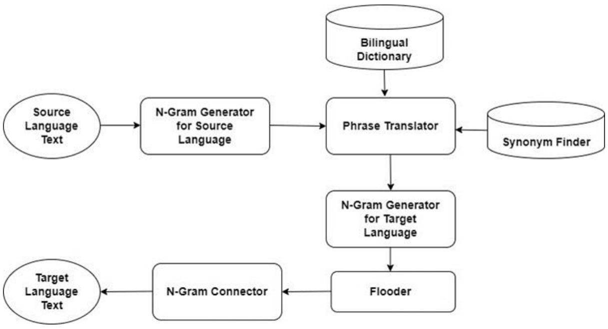

Fig 11: Context-Based Machine Translation Approach

3.5 Hybrid Machine Translation Approach

Hybrid machine translation approach that is designed by combining methodologies in both statistical and rule-based translation approaches. This approach offers better efficiency as it has been developed by taking advantage of two machine translation approaches. There are two common forms in this approach. The first one is rules post-processed by statistics where translations are produced using a rule-based engine while statistics are used to adjust and correct the generated output from the rule-based engine. This method is also known as statistical smoothing and automatic post editing. The second form is statistics guided by rules where rules are used to pre-processing and post-processing with the help of statistical engine. This technique has more power, control, and flexibility in translation than first form. Furthermore, this approach has several models such as word-based, syntax-based, phrase-based and forest-based.

3.6 Agent-Based Machine Translation Approach

This approach is a new paradigm to machine translation. In this technique, agent technology or multi-agent systems technology will be used to handle the translation. Generally, multi-agent systems comprise four main components such as multi-agent engine, ontology, interfaces, and virtual world. In there, multi-agent system is responsible with providing run time support for the agents while ontology describes the domain knowledge of the agents and virtual world is the environment of the multi-agent system. In this environment, agents are working cooperatively to achieve a given task. Using this concept, at present, many translation systems have been developed. Many of these translation systems use this power of agent technology to handle the semantics part in the translation.

3.7 Neural Machine Translation Approach

Neural machine translation approach is the latest and dominant paradigm to the field of machine translation. It has achieved state-of-art performance for many language pairs and at present, many machine translation systems have been developed or modified using this novel approach. Unlike other machine translation approaches that are comprised of many individual components, this new approach tries to build and train a single complex neural network to produce a high-quality translation. Moreover, deep neural machine translation is an extension of existing neural machine translation. The difference between shallow NMT and deep NMT is that shallow NMT contains a single neural network layer while deep NMT has many layers. Deeper layers increase the learning capacity and lead to better quality and accuracy of the translation [14].

In contrast, all of these machine translation approaches can be compared in respect to various evaluation metrics such as BLEU (Bilingual Evaluation Understudy) scores, METEOR (Metric for Evaluation of Translation with Explicit ORdering), TER (Translation Edit Rate), CHRF (Character n-gram F-score), GLEU (Google BLEU) and BERT Score. Among them, these machine translation approaches have been compared by considering BLEU score metrics. Table 1 provides the summary of comparison of machine translation approaches respect to the BLEU score metrics.

Table 1. Comparison of Machine Translation Approaches

Machine Translation Approach	BLEU Score Ranges
Dictionary Based Machine Translation Approach (DBMT)	10-25
Human Assisted Machine Translation Approach (HAMT)	50-80
Rule Based Machine Translation Approach (RBMT)	10-30
Statistical Machine Translation Approach (SMT)	20-40
Example-Based Machine Translation Approach (EBMT)	10-45
Context-Based Machine Translation Approach (CBMT)	35-55
Hybrid Machine Translation Approach (HMT)	25-50 [RBMT + SMT = 25-40] [SMT + NMT = 35-50] [RBMT + NMT = 30-50] [Adaptive Hybrid Systems = 40-50]
Agent-Based Machine Translation Approach (ABMT)	20-45
Neural Machine Translation Approach (NMT)	30-50

4. KNOWLEDGE REPRESENTATION

Knowledge representation is one of the key concepts in Artificial Intelligence (AI) which was very rare to find a clear and direct explanation [15]. However, this concept was explained using five points or five roles such as;

- It is a surrogate that is a substitute for something itself which is used to determine consequences by thinking and reasoning about the world rather than acting on it.
- It is a collection of ontological commitments which describes how to think about the world.
- It is a fragmentary theory of intelligent reasoning that can be further described using three components such as representation of basic concept of intelligent reasoning, collection of inferences that explain sanctions of the representation and a bundle of recommended inferences.
- It is an approach for pragmatically efficient computation.
- It is a medium of human expression that can be used as a language to express things about the world.

Nevertheless, the concept of knowledge representation can be simply explained as the process of representing knowledge in a structured and organized format that can be used by computers to process efficiently and to reason about knowledge. There are several goals in knowledge representation such as it is mainly used to acquire the expressive power of human knowledge such as concepts, relationships in a particular domain using some of the limited capabilities such as understanding, processing speed and computer memory. Secondly to permit different types of reasoning that are deduction, induction, and abduction and thirdly to facilitate knowledge catering and reuse. Moreover, it mainly aims to support knowledge-based decision making, to enable develop and maintain intelligent systems and to make plausible conclusions.

There are three main categories in knowledge representation such as representation knowledge, reasoning knowledge and form knowledge. Representation knowledge describes the capability of the computer system to understand data which are inputted or stored on them. Accordingly, representation knowledge requires realizing various types of data types such as text, images, videos that are converted into formats suitable for machine learning algorithms. Secondly, reasoning knowledge specifies the way computers interact with given information and rules to come up with conclusions using those facts. Moreover, it can be defined as a cognitive process that involves logic and critical thinking to understand information to solve problems or to make decisions. Form knowledge refers to the representation of large sets of complex problems using mathematical models such as Pico Framework or Expert Knowledge Representation Languages (EKRL) [16].

5. KNOWLEDGE REPRESENTATION TECHNIQUES

Knowledge representation applications spread across various domains such as Semantic Analysis, Machine Translation and Question Answering in the area of Natural Language Processing, Expert Systems, Robotics, Semantic Web and Ontologies, Cognitive Computing and Reasoning, Multi-agent system technology and etc. In this section, we are considering different knowledge representation techniques and explore how these techniques support the machine translation process [17].

5.1 Logical Representation

Logical representation expresses all the information using logic. These logics give a processable form to all the information that can be precisely expressed in any other language. In this method, each sentence or phrase will be transformed into logic(s) using syntax and semantics. Logical representation can be broadly classified as propositional logic and predicate logic [18].

Propositional logic or Boolean logic is the simplest form of logic where all the statements are constructed by propositions that is a declarative statement which is either true or false. Further, the syntax of propositional logic defines the allowable sentences for the knowledge representation. There are two types of propositions such as atomic propositions and compound propositions. Predicate logic came to the stage to overcome the drawbacks and issues of the propositional logic. When using propositional logic, it is very difficult to represent complex sentences and natural language statements. In addition, propositional logic has very limited expressive power. As a result of this, predicate logic has been used as an extension of propositional logic.

Logical representation supports machine translation by understanding sentences semantically, handling syntactic variations, expressing semantic roles and maintaining consistency.

5.2 Semantic Network Representation

Semantic-network representation or propositional net is a net which is a graphic notation to represent knowledge in patterns of interconnected nodes and arcs [19]. The nodes of the network represent objects while the arcs describe the relationship between those nodes. Moreover, this technique is an alternative to predicate logic knowledge representation. These networks are easy to understand and can be easily extended. Besides, semantic network representation computer implementations have been first used in artificial intelligence and machine translation. Furthermore, this technique allows to perform inheritance reasoning as all the child classes will inherit all the properties of parent class and allow multiple inheritance.

Semantic network representation supports machine translation by properly capturing relationships and meanings, handling syntax and grammar differences, and improving accuracy of complex sentences.

5.3 Frame Representation

Frame representation is also known as filter knowledge representation. The main aim and purpose of this representation is to put pieces of detailed information about an entity. When considering a frame, it is an AI data structure which contains a set of attributes and appropriate values to describe an entity that is available in the real world. Moreover, it divides knowledge into sub-structures by representing stereotypes situations. Accordingly, frame contains a collection of slots and appropriate slot values which are named as facets. Generally, these frames are derived from semantic networks and evolved as classes and objects. When considering a single frame, it is not much useful and a frame system has a collection of frames that are interconnected. Frame representation supports machine translation by handling contextual role assignments, handling ambiguity, supporting fixed and idiomatic expressions, and providing syntactic flexibility.

5.4 Production Rules

Production rules mainly contain (condition, action) pairs. That means, "if condition then action". Basically, it has three parts such as set of production rules, working memory and the recognize-act-cycle. In this technique, firstly it checks for the condition and if the condition exists, then production rule fires to the suitable action that should be needed to carry out. Further, the condition part determines which rule to be applied while action follows the necessary problem-solving steps. Then, this whole complete process is named as recognize-act-cycle. The working memory contains a detail description of the current state and rules can add knowledge to this memory. This knowledge matches and fires other rules. Whenever, new situation or state generates, then multiple productions rules will be fired together that is named as conflict set. Moreover, in this situation, it is needed to select a rule, and it is named as conflict resolution. Production rules also play a significant role in machine translation by properly handling syntax variations, handling idioms and fixed expressions, adjusting morphological elements, and reducing errors in complex sentences.

There are some latest knowledge representation techniques that were discovered in recent years. Among them, most of them use neural networks and deep neural networks. A brief explanation about these techniques are discussed below.

5.5 Graph Neural Networks

A graph neural network or GNN is one of the classes of artificial neural networks that are represented as graphs to process data. The general architecture of the graph neural network is comprised of three fundamental layers such as Permutation equivariant, local pooling and global pooling. Graph Neural Networks are used to capture structural information inherently and can be used to store this information in these graphs. At present, graph neural networks have obtained significant attention for their great capability to capture relationships and dependencies between elements of the graph and making them well-suited in knowledge representation [20]. More specifically, in the machine translation point of view, GNNs can be used to represent the information of a sentence using nodes and edges such as words or phrases as nodes while relationships between words as edges [21]. Furthermore, different open-source libraries have been implemented considering the theory of graph neural networks such as PyTorch, TensorFlow GNN and Google JAX [22].

5.6 Transformer Based Models

A transformer is a deep learning model which follows encoder-decoder architecture. that can automatically transform one type of input into another type of output. Also, transformers are like Recurrent Neural Network (RNN) models as they are mainly designed to process sequential data such as natural languages with supporting the applications namely machine translation and text summarization. Accordingly, these transformer-based models are used to store and represent language knowledge of these natural languages to support machine translations and text summarization tasks. Therefore, transformer based models support machine translation tasks in several ways by capturing context, speeding up the translation using parallelization, positional encoding to retain word order, handling long range dependencies, offering scalability, and accurately handling polysemy and ambiguity[23].

5.7 Knowledge Graph Embeddings

Knowledge Graph Embeddings or KGEs is a directed heterogeneous multigraph. There is a relationship between knowledge graph and knowledge graph embeddings (KGEs). That is KGEs are low-dimensional representations of the entities and relations in a knowledge graph while preserving their semantic meaning. Moreover, these knowledge graph embeddings are also known as knowledge representation learning (KRL), or multi-relation learning that can be described as a machine learning task. Moreover, Knowledge Graph Embeddings (KGEs) support machine translation by enriching models with structured, semantic knowledge. That is, it enhances context understanding as it contains rich semantic and relational data about words, entities, and their connections. Secondly, it help disambiguate by providing additional context from a knowledge graph, which has connections between entities. There are different KGE models such as TransE, TransR, RESCAL, DistMult, ComplEx, and RotatE, that have different score functions to learn entity and relation embeddings [24].

5.8 Ontologies

Ontologies are very familiar in NLP, knowledge engineering, knowledge management, and cooperative information systems that can be explained as a standard specification of the domain that presents knowledge based on conceptualizations. Mainly, they are very useful in knowledge organization and representation. There is a difference between ontologies and databases. That is, ontologies are richer syntactically and semantically than approaches in databases. Furthermore, databases contain semi-structured texts written in natural languages and ontologies facilitate with domain theory rather than providing a data container. Ontologies play a crucial role in supporting machine translation (MT) by providing a structured, semantic framework that helps models better understand, disambiguate, and translate language. An ontology defines the relationships between concepts, entities, and terms in a domain, offering a rich source of contextual and semantic information. This structured knowledge helps machine translation systems improve their performance, especially when dealing with complex, domain-specific, or ambiguous language. [25].

5.9 Probabilistic Graphical Models (PGMs)

Probabilistic graphical model is a graphical construction-based model that shows probability-based relationships among random variables. Moreover, it is based on Bayesian rules. This concept was first explored and proposed in 1990 by J. Whittaker from the statistics point of view and in recent years, PGM has become trending research in the areas of machine learning, artificial intelligence and data mining as it acts as an effective tool to solve complex problems. PGM is not a single discipline, and it is a combination of probability theory and graph theory. Also, PGMs support machine translation by providing a probabilistic framework that handles word alignments, syntactic structures, long-range dependencies, and contextual information. Moreover, it manages uncertainty and ambiguity, improving translation accuracy by modeling the complex dependencies between words and phrases in both the source and target languages [26].

5.10 Deep Generative Models

Deep generative models are one of the classes in machine learning and have become a trending research area in AI to open novel possibilities in creative AI and data generation. It is a neural network containing many hidden layers to generate new data sets that resemble a given training dataset. Generally, DGMs are based on deep neural networks, and they can capture complex patterns in the data set. Although there are many different types of deep generative models, generative adversarial networks (GANs) and variational autoencoders (VAEs) are considered as the most famous DGMs. Generative adversarial networks have two neural networks, namely generator and discriminator while variational autoencoders are a category of autoencoder that is a neural network architecture in unsupervised learning. Moreover, deep generative models are used in different applications including knowledge representation, image synthesis, text generation, data augmentation etc [27]. Also, it supports machine translation by modeling the underlying distributions of language, generating diverse and fluent translations, and handling challenges such as ambiguity, long-range dependencies, and low-resource languages. DGMs like VAEs and GANs enable the generation of coherent, contextually appropriate translations while capturing the nuances of style, tone, and fluency.

6. EXPLORING MACHINE TRANSLATION APPROACHES AND KNOWLEDGE REPRESENTATION TECHNIQUES IN DIFFERENT MACHINE TRANSLATION SYSTEMS

It is very important to mix a proper machine translation approach with appropriate knowledge representation technique to develop an efficient, successful, and well-performed machine translation system. This is because proper knowledge representation technique helps to easily handle ambiguity resolution, Idioms and Colloquialisms, named entities, polysemy, to incorporate world knowledge, adapting to specialized domains, and to improve fluency and coherence.

This chapter aims to review some of the most widely used machine translation systems in the world to study their machine translation approach and knowledge representation technique. Accordingly, we have deeply studied about 20 famous machine translation systems and Table 2 shows the summary of these machine translation systems [28][29][30][31][32][33][34][35][36][37][38][39][40][41][42][43][44].

Table 2. Summary of Machine Translation Systems

Machine Translator	Machine Translation Approach	Knowledge Representation Technique
Google Translator	Neural Approach	Recurrent Neural Networks Transformer based Models
DeepL Translator	Neural approach	Convolution neural network models
Microsoft Translator	Neural approach and Statistical Approach	Recurrent neural networks Deep transformer-based models n-gram models
Amazon Translator	Neural Approach	Recurrent Neural Networks Transformer based Models
Watson Language Translator	Neural approach and Statistical Approach	Phrase-based statistical models Sequence-to-sequence statistical models Recurrent neural networks Transformer models

Unbabel	Neural approach	Machine learning models
TranslateMe	Neural approach	Blockchain knowledge management models
Yandex Translate	Neural approach and Statistical Approach	Deep neural network models
Language Weaver	Neural approach	Transformer-based knowledge representation
Azure Translator Text API	Neural approach	Vector representation model
Lingvanex Translator	Neural approach	Machine learning models
Personal Translator – Linguatec	Hybrid approach (Rule-based approach + statistical approach neural approach)	Semantic Networks
Language Studio	Deep neural approach and Statistical approach	Recurrent neural networks Deep transformer-based models n-gram models
TextShuttle AI Translation	Neural approach	Deep learning models
Babylon	N/A	N/A
GramTrans	Rule-based approach – Transfer-based approach	Production rules
Alexa Translations A.I	Neural approach	Deep learning models
Apertium	Rule-based approach – Transfer-based approach	Production rules Hidden Morkov models
OpenLogos	Rule-based approach	Logical forms Production rules
Systran	Neural approach	Deep learning models

7. FUTURE DIRECTIONS OF MACHINE TRANSLATION ALONG WITH KNOWLEDGE REPRESENTATION

Novel methodologies for machine translation (MT) that incorporate knowledge representation are becoming more tremendous and advanced as they seek to improve translation accuracy, context-awareness, and handling of complex language structures. Knowledge representation (KR) involves encoding information about the world, language, and entities in a structured, machine-readable form, such as ontologies, semantic graphs, or symbolic logic. Therefore, these methods help machine translation systems to understand and process meaning, enabling translations that go beyond simple word-for-word substitution. A brief description of some emerging methodologies that integrate machine translation with knowledge representation are described below.

7.1 Neural-Symbolic Machine Translation

Neural-symbolic systems can be introduced as a hybrid system that combines the strengths of neural networks with symbolic reasoning. Therefore, this approach leverages the pattern recognition capabilities of neural networks along with the structured, rule-based reasoning found in knowledge-based systems. Furthermore, in this approach, neural models handle translation tasks such as sentence parsing and generation, while symbolic reasoning processes linguistic rules and world knowledge.

7.2 Ontology Enhanced Machine Translation

Ontologies can be integrated into machine translation systems to accurately map source language phrases to their corresponding concepts in the target language. The system can then generate translations that account for the relationships between concepts, improving both translation quality and semantic accuracy. Furthermore, it can be subdivided into two types such as domain-specific ontologies and multilingual ontologies. Domain-specific ontologies will tailor to specific fields such as medicine, law, engineering to ensure precise translations of technical terms and concepts while multilingual ontologies provide mappings between concepts in different languages, facilitating better cross-lingual translation by understanding the underlying semantics of terms rather than relying purely on statistical methods.

7.3 Graph-Based Machine Translation

Graph-based representations such as knowledge graphs or semantic graphs model relationships between entities, concepts, and actions in a structured way. These graphs enable machine translation systems to capture the deeper meanings and relationships in text, improving translation by considering contextual information. Therefore, graph-based machine translation systems improve the handling of coreference and disambiguation, ensuring that complex sentences are translated accurately.

8. CONCLUSION

This paper presented a broad discussion about knowledge representation strategy in machine translation. It was realized that knowledge representation scheme in a machine translation system is closely related with the machine translation approach. The importance of combining machine translation along with knowledge representation is that this combination will leads to properly understand, process and generate human languages effectively. Also, it helps to handle complexities, understanding semantics, enhance syntactic and grammatical accuracy, handle idioms and handle ambiguities. Therefore, we reviewed some latest and popular machine translation systems in the world and identified that most of them have been developed using the neural machine translation approach or using a hybrid approach as the machine translation approach while using deep neural network models or transformer-based models as the knowledge representation technique. The reason for using the neural machine translation approach along with such deep neural network models are that they offer some advantages over classical approaches including contextual understanding, great quality and fluency as these models capture complex language patterns, helps to handle long range dependencies while maintain correct context and meaning of texts, high scalability due to large training datasets, multilingual capabilities within a single framework, continuous improvement from continuous learning, handling ambiguity and polysemy, parallel processing, robustness and rich representations.

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