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Artificial Intelligence in Translation and Interpreting

Grado en Traducción e Interpretación: Inglés-Alemán

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3. **Affidavit**: at the end of the document, we include an affidavit in which we declare to make use of good academic practices in each and every aspect of this work.

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Table of abbreviations

Abbreviation	Full form
AI	Artificial Intelligence
ANN	Artificial Neural Network
ASR	Automatic Speech Recognition
CAT	Computer-assisted Translation
CBMT	Context-based Machine Translation
DBMT	Dictionary-based Machine Translation
DL	Deep Learning
EMBT	Example-based Machine Translation
FAMT	Fully Automated Machine Translation
HAMT	Human-aided Machine Translation
KBMT	Knowledge-based Machine Translation
MAHT	Machine-aided Human Translation
MI	Machine Interpreting
ML	Machine Learning
MT	Machine Translation
MT-A	Machine Translation for Authors
MT-R	Machine Translation for Revisers
MT-T	Machine Translation for Translators
MT-W	Machine Translation for Watcher
NLP	Natural Language Processing
NLG	Natural Language Generation
NLU	Natural Language Understanding
NMT	Neural Machine Translation
PE	Post-editing
RBMT	Rule-based Machine Translation
SL	Source Language
SMT	Statistical Machine Translation
TL	Target Language
TM	Translation Memory
TTS	Text-to-speech

Abstract

The presence of Artificial Intelligence (AI) is becoming increasingly important in translation for the present and future translators. Computer-assisted translation (CAT) tools already provide translators with an excellent source of help, and the professionals who have proficiency in the use of these tools are able to increase the quality of their translations and reduce the time required to perform repetitive tasks. As well as for translators, advances in technology also make possible for interpreters to take advantage of AI-powered tools, such as text and speech recognition to assure quality. AI and its sub-branches, such as Machine Translation, Natural language Processing and Deep Learning are extremely crucial for translators. Having theoretic knowledge and knowing how to use these tools will provide both translators and interpreters with important opportunities.

Key words: Artificial Intelligence, Machine translation, Natural Language Processing, Computer assisted translation.

Resumen

La presencia de la inteligencia artificial (IA) en el mundo de la traducción e interpretación va cobrando cada vez más importancia para los profesionales del campo. Las herramientas de traducción asistida por ordenador (TAO) ya proporcionan a los traductores una excelente fuente de ayuda y son los profesionales capaces de manejarlas los que consiguen aumentar la calidad de sus traducciones y reducir tiempo en ejecutar tareas repetitivas. Al igual que para los traductores, los avances en la tecnología hacen que los intérpretes también puedan sacar provecho de herramientas basadas en la IA, tales como herramientas de reconocimiento de texto y voz. Las subramas, como la traducción automática, el procesamiento del lenguaje natural y el aprendizaje profundo son instrumentos de suma importancia para los traductores e intérpretes que quieran desarrollarse con vistas al futuro de la profesión. Aprender a usarlas o tener conocimiento teórico acerca de ellas, proporcionará importantes oportunidades a los profesionales de la traducción e interpretación.

Palabras clave: inteligencia artificial, traducción automática, Traducción asistida por ordenador, procesamiento del lenguaje natural.

1. Introduction

Intelligence is something that has always defined human beings and is considered a quality inherent to the species. For hundreds of years, human beings have used intelligence to understand, ask, and give answers to existential questions that have allowed the development of today's technology and society. Artificial intelligence (AI) grows from the human need to solve problems that require a certain degree of intelligence to be executed in the same way as a human being would. AI systems are able to assist a wide range of problems such as language learning solutions, diagnosing diseases, or fraud detection. Its design and aim are based on the human brain to mimic features of human intelligence, such as the ability to learn, solve problems and communicate through language. As technology has developed exponentially throughout history, first with the creation of computers and then with the internet revolution, AI has not stopped progressing either. From the question of whether a machine is capable of thinking to the creation of virtual assistants, AI has undoubtedly become an unstoppable discipline with an enormous potential. According to Abiodun et al. (2018) "Artificial intelligence (machine learning, neural network, deep learning, robotic), information security, big data, cloud computing, internet, and forensic science are all hotspots and exciting topics of information and communication technology." (p. 2). AI is rather a young discipline and differs from others such as psychology or philosophy in the fact that AI researchers are not only able to study the external behavior but instead, they experiment with physical models. Modern computers and AI researchers create tangible solutions to problems philosophers were only able to provide theories (Poole & Mackworth, 2010 , p. 9).

However, AI also brings challenges to disciplines such as translation and interpreting. Machine learning and natural language processing led to the generation of innovative approaches such as neural machine translation (NMT) and automatic speech recognition (ASR) tools for interpreters. While these emerging technologies are currently being discussed in the science and communities of practice, technology giants such as Google LLC (Alphabet Inc.) and IBM Corporation heavily invest in translation and interpreting AI-driven technology to bring outputs closer to high quality human translation and interpreting. Applications for accessibility such as text-to-speech (TTS) systems and essential tools for translators such as post editing instruments are present in professional and daily tasks as many of them provide an easier outcome to solving problems. One of the biggest concerns translators and interpreters have to deal with is communication, since professionals translate texts and interpret discourses to reduce barriers between languages. AI applications, such as machine translation, are capable of getting information from one language to another by using AI-powered translation technology.

AI applications are dramatically changing the translation and interpreting industry. However, AI-powered translation tools are still not able to provide excellent results where the result of a human translation is comparable to the one of a machine, but technology is getting remarkably close. Globalization, the Internet, and the development of AI-powered tools have raised expectations of professional translators and interpreters and those who want their services. High-quality translation, speed, and adaptability have become less relevant skills as part of the translator's background due to the impact of AI in the industry. These skills that were previously used as a differentiating element for translators and interpreters are now considered an unquestionable resource for any translation graduate. With the exponential growth of AI in many expertise fields, professional translators and interpreters are expected to have additional knowledge and experience in relevant and complementary areas that can benefit companies and clients.

2. Objectives and methodology

The present BA thesis has two objectives: to explain how AI has progressed throughout history, particularly in the history of translation and interpreting; and to explain the applications and impact of AI in the field of translation and interpreting. To achieve these objectives, attention will be paid to definitions of the most relevant AI concepts, as well as pertinent terminology. The history of AI from the early years to the present day will also be introduced, followed by the state of the art that will give an introduction about the latest AI trends. AI approaches and applications will also be explained, as well as the relationship of AI to the field of translation and interpreting. Finally, a conclusion will be provided to discuss the possibilities and future approaches of AI, as well as the translation and interpreting expectations and future trends. The advantages and disadvantages of using AI-powered tools in translation and interpreting will also be discussed as part of the conclusion.

All the bibliographical references used in this BA thesis were chosen following the criteria of relevance and quality. To decide the relevance of a reference, i.e., whether the source fits the topic, attention was paid to its introduction and conclusion, as well as the explanation of the different topics and their degree of relevance given by the author. On the other hand, the quality of the source was ensured by looking through internet published documents that were signed and affiliated to an academic institution or cited by many other authors. As for the images, most of them are from previously consulted sources, such as figure 1 used to explain the AI ecosystem, which was extracted from the ISO standard No. CD 22989. This methodology is applied as images from previously consulted sources provide a more accurate representation of the explanation. However, there are some images retrieved from other sources, such as online articles, when images from previously consulted bibliography were not available.

The publication manual used in this thesis to cite the authors of the sources has been the American Psychological Association (APA). This manual was selected to provide consistency and give detail of ideas being discussed to the readers. On the other hand, US English has been chosen to author this paper because it has been more studied and widely used by the author than other varieties of English.

As for the process followed to write this document, the following sources were used ranked in order of priority:

1. International Standards
2. Technical and scientific books
3. Theses and other academic publications
4. Technical and scientific journals
5. Dictionaries and encyclopedias
6. Blogs and similar publications

The material used was selected through a process of checking reliable and, above all, updated sources. However, books and journals written years apart have also been used to have access to a global view of the impact of this topic over the years.

The first steps to write this BA thesis were the terminological documentation and settlement of the terms with the help of the ISO/CD 22989. Attention was paid to the ISO standards to gather terminological information, since it is the most well-grounded institution that provides this specific content for this work. ISO standards provide well-structured information about the terminology of the standard as well as definitions for every relevant concept of the topic, which constitutes an exceptionally dependable source to be the main part of the bibliography research. The ISO standards are elaborated by experts from all over the world who are carefully nominated and selected by national standards bodies. The ISO standards are submitted to very severe multiple-step reviews over years before publication, which is why they are a reliable and important source to include in this document.

When the terms were established, the process continued with the documentation of the history of AI and the progress made during the first years until the present, as well as its diverse subbranches. For this part, it has been consulted mostly technical and scientific books, which were carefully chosen to provide different perspectives as well as comparisons between related disciplines. Since AI is found in many areas of knowledge, it was pertinent to collect information from different disciplines related to AI to provide a broader perspective to the topic. Books by mathematicians, philosophers and computer scientists from different decades were selected showing a wide range of opinions and points of view in order to understand what AI means in different domains.

The following procedures consisted of gathering information from academic publications, which were mainly theses, scientific essays, scientific and technological articles from various sources. The main purpose of the information retrieval was to be able to contrast all the sources and have a large view of the field. The next step was to decide whether the information chosen is relevant to the topic and research the veracity of the source. The sources went through a selection process where those with quality information on translation and interpreting in relation to the field of AI were kept. Most of the academic publications and technical journals were selected through Google Scholar tool since it provides open-access academic materials. However, the university library was also consulted for academic publications and technical books.

Dictionaries and encyclopedias were consulted when the preferred sources could not provide the information needed. They were mainly examined in order to introduce the topic, as well as to compare terms to have more information in order to understand and familiarize with the terms. Information found in specific dictionaries and encyclopedias were mostly contrasted with the ISO standard to have a guide whether the terms were settled and understood.

Finally, more information was retrieved from blogs and similar online articles affiliated to an institution or written by renowned authors. These sources were mainly consulted to gather up-to-date information about recent applications of AI and future trends, as well as specific crucial information unavailable in other sources.

3. Theory

3.1 Terms and definitions

To understand the concept of AI, a definition of intelligence must be given. According to Jones, intelligence can be defined as "a set of properties of the mind" including the use of intuition, knowledge, plausible reasoning, creativity, common sense, and judgement (2008, p.1). Alternatively, other authors point out that humans have limited intelligence, since how the human brain process information is slower when compared with data processing capability of today's high technology computers. The author also explains that animals have intelligence too, which makes it a characteristic not unique to the human mind. The properties of an intelligent mind include the ability to solve problems, communicate by language, and learn.

There are two of the ways people are able to prove intelligence, which can be done in two related ways:

- Through communication
- Through learning, which is acquiring knowledge through experience and be able to prove it through communication (Tanimoto, 1990 , p. 4).

Another practical definition of intelligence given by Jones is the ability to make the right decision through a series of input factors and actions. The latter definition of intelligence, i.e., the ability to make decisions, is a much more complex process when associated to the human mind. There are capabilities, such as learning and adapting, that animals have much less developed in comparison to humans. If used the same analogy with intelligent machines, it can be seen that there are machines that are experts in very particular things, such as board games, but lack every other intelligent skill and still can be considered intelligent (2008, p. 1-2).

Now that the definition of intelligence is cleared, a definition of AI should be introduced. According to Dean et al. AI is defined as "the design and study of computer programs that behave intelligently, which are constructed to perform as a behavioral intelligent human or animal would.” (1995, p. 1). Another definition of AI is the technology by which an intelligence similar to human is artificially created (Zheng, & Zhu, 2020 , p. 1). On the other hand, ISO/CD 22989 makes a breakdown of AI approaches and introduces the definition of AI as a discipline, which defines it as the “study of theories, mechanisms, developments and applications related to artificial intelligence.” (ISO, 2021, 3.1.3). However, to provide a general definition of AI, Lu states that “any theory, method, and technique that helps machines (especially computers) to analyze, simulate, exploit, and explore human thinking process and behavior can be considered as AI.” (2019 , p. 1).

The study of theories has led AI to encounter with many different fields, including philosophy. The presence of philosophy in IA provides an introduction of two approaches: the “weak AI” and the “strong AI.” According to ISO/CD 22989, the “weak AI” system can only process information without understanding what is doing. The “strong AI” system, however, also processes information, but understands what is doing (ISO, 2021, 5.2). According to Russell and Norvig, it is shown in a resume about weak and strong AI, that philosophers use the term “weak AI” for the hypothesis that machines could behave intelligently, and “strong AI” for the hypothesis that such machines would count as having actual minds (2010, p. 1020). ISO/CD 22989 points out that the designations "weak AI" and "strong AI" only matter in the realm of philosophy and are of little relevance to AI researchers.

Philosophy also made a distinction of what is known as "narrow AI" in contrast to "general AI". A "narrow AI" system is capable of completing define tasks to solve a specific problem, which is what the present-day AI systems are able to do. On the other hand, the "general AI" system would have the ability to do any task that requires AI with satisfactory results. However, it is still unknown whether the "general AI" systems will be practical in the future (ISO, 2021 , 5,2).

Along with the definitions of intelligence and AI, there is another pertinent term that should be introduced, which is the AI Agent. ISO/CD 22989 defines Agent as an “automated entity that perceives its environment and achieves its goals.” An AI agent maximizes its chance of successfully achieving its goals by using AI (ISO, 2021, 3.1.1). Russell and Norvig state that an agent is an entity that acts on something. A Computer Agent is able to run autonomously, perceive their environment, adapt to change, and improve its performance by learning. Intelligent agents make decisions based on experience and its environment (2010, p. 4). There are also definitions of AI that mention the agents since they constitute an important part of the system. Poole and Mackworth define AI with an agent-focused perspective stating that "AI is the field that studies the synthesis and analysis of computational agents that act intelligently." (2010, p. 3).

3.2 History of artificial intelligence

3.2.1 Philosophy

AI, to a significant extent, belongs to the field of philosophy. Some of its roots come from questions that philosophers have been asking for thousands of years. An example is how Hobbes and Leibniz thought about breaking down the mind into small operations in a mechanical way (Dennett, 1988, pp. 283-284). Descartes also took part with the prediction of the Turing test, showing it in his book *Discourse on the Method*:

> The first is that they would never be able to use words or other signs by composing them as we do to declare our thoughts to others. For we can well conceive of a machine made in such a way that it emits words, and even utters them about bodily actions which bring about some corresponding change in its organs […] but it is not conceivable that it should put these words in different orders to correspond to the meaning of things said in its presence, as even the most dull-witted of men can do (Descartes, 1637/2006, pp. 46-47).

However, from this book one can also draw the conclusion that Descartes denied that machines could become intelligent, stating that even the most dull-witted of men can surpass its intelligence.

3.2.2 Early years (1943-1950)

One of the earliest works of AI was done by Warren McCulloch and Walter Pitts in 1943. Their work was focused on three main points: the study of psychology and how neurons work in the brain; an analysis of the propositional logic, and a study of Turing's theory of computation. The study based on those three sources led to the creation of a model of artificial neurons, which were capable of switching "on" and "off." Later it was discovered that the "on" state occurred as a response to stimulation of the neighboring neurons (Russell & Norvig, 2010, p. 16).

Following the McCulloch and Pitts research, a study of how computers can help with the translation of natural languages began. It was in 1947, when the member of the Rockefeller Foundation, Warren Weaver wrote a letter to the Cybernetician Norbert Wiener explaining innovative ideas for the study. Two years later, Weaver wrote an article presenting different proposals based on four sources: the success of code breaking during war; the information theory developed by Claude Shannon; the speculation of the principles of natural language; plus, a personal thought on how to make the idea of a translating machine into reality (Hutchins, 2015, p. 120). In the same year, Donald Hebb, a physiologist at McGill University, introduced the idea that neural networks cannot only compute, as McCulloch and Pitts had stated, but also learn. Hebb was the one who proposed the theory that brain connections change as different tasks are learned through synapses (Trillas, 1998, p. 61). A year later, in 1950, Machine translation (MT) began to show progress when the three basic approaches of MT were developed: the direct translation approach, the interlingua approach, and the transfer approach (Hutchins, 2015, p. 120).

3.2.2.1 Alan Turing

On the present day, there are many works that talk about AI, but the vision and work of the mathematician Alan Turing remains as one of the most influential works on this field. Turing had been giving lectures about AI and mathematics since 1947, and it was in 1950 when he published an article called *Computing Machinery and Intelligence*. In this article, he describes how to create an intelligent machine and evaluate its intelligence (Russell & Norvig, (2010 , p. 17). He wondered if it could be possible that by asking a question to a machine, it would be able to answer in an equivalent way as a human. With this premise and his mathematical knowledge, he created what is known as the *Turing Test*, an experiment to evaluate whether a machine could be considered intelligent. The test consists of a series of questions that challenge the computing machine about different skills such as mathematics and problem solving to evaluate its intelligence. It was said that if the machine, during the *Turing Test,* gave responses and acted in such a way that it could make a human believe that the machine was also a human, it passed the *Turing test*, which means that the machine possess intelligence. During this period, Turing realized that what was really important was not to materialize intelligence into a computer, but to make this intelligence grow in the same way as a child does throughout its infancy to reach the complex mind of an adult. Turing explains his ideas throughout his article *Computing Machinery and Intelligence* his innovative ideas of creating a mind that can be educated:

> Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulates the child´s? If this were then subjected to an appropriate course of education one would obtain the adult brain. (Turing, 1950, p.456).

Turing realized that instead of assuming that a rich, adult intelligence must be created, one could mimic the education and learning experience the same ways as a human being by creating a child without any knowledge but the ability to obtain it. A child is not born with the same knowledge that will have in its adult phase, but instead it obtains it through learning and experience. Turing proposed the *Child Machine* as a project to create an unintelligent agent with the ability to learn through a system of education. (Jones, 2008, p. 3).

3.2.3 The beginning of artificial intelligence (1956- 1979)

3.2.3.1 The Dartmouth Conference (1956)

The word Artificial Intelligence was settled in 1956, six years after the creation of the *Turing Test*. It was developed during the Summer Research Project on AI at Dartmouth college, organized by Marvin Minsky and the Stanford computer scientist John McCarthy. The aim of this summer project was to bring specialists from different areas to research on the field of AI and discuss the future of the discipline. Computer scientist Nathaniel Rochester, the designer of IBM 701, and mathematician Claude Shannon, who developed the information theory, were some of the participants. This summer research project would later be known as the Dartmouth conference, where the beginning of Spring AI started. This advance in the field was crucial for AI development and those who took part in the conference are now known as the founding fathers of AI (Haenlein & Kaplan, 2019, p. 7).

3.2.3.2 LISP Language

To be able to create, control and communicate with AI in computers, it was necessary to learn its language, which is to say, it was important to know how to use programming languages. The use and knowledge of the programming language LISP was especially essential since it is related to AI. The LISP language was developed by John McCarthy in late 1950s. It appeared during the early days of AI and is one of the oldest programming languages still in use today. LISP language was originally created as a practical mathematical notation for computer programs and was designed to manipulate symbolic information. LISP Stands for LISt Processing since the linked lists are one of LISP's biggest data structures, as well as a hint that LISP source code is structured in lists. In addition, data and programs are also represented as lists of lists (Jones, 2008, p. 443). The LISP language is made out of various function definitions, written by a text editor, along with other statements that work together to perform a task (Tanimoto, 1990 , p. 15-16).

John McCarthy introduced at Massachusetts Institute of Technology (MIT) the ideas on which LISP is based in 1958. Two years later, in 1960, he published an article called *Recursive Functions of Symbolic Expressions and their Computation by Machine, Part I,* as a base for the LISP language (Tanimoto, 1990, p. 15).

3.2.3.3 The discipline post-Dartmouth Conference (1960 – 1979)

AI continued making incredible progress after the Dartmouth Conference. Proof of this is the conversational chatbot ELIZA, created by John Weizenbaum between 1964 and 1966 for the MIT. This conversational chatbot was one of the first machines who passed the *Turing Test,* which is to say, it was considered intelligent. ELIZA was capable of processing natural language and having simple conversations with a human (Haenlein & Kaplan, 2019, p. 7).

Remarkable advances were made since AI started to take part in translation and interpreting. In the late 1950s MT research was generously funded by the U.S. National Research Council to speed up the translation of Russian scientific papers about the launch of Sputnik, the world's first artificial satellite (Russell, & Norvig, 2010, p. 21). Years later, in the 1960s, the translation demand grew in the United States and the Soviet Union. The translations needed were mostly technical in both linguistic combinations, Russian-English and English-Russian, and were made for an exclusive number of important users. The main purpose of the translations was to understand what was written, therefore, the recipients overlooked terminological, grammatical, and style errors. However, the trend of overlooking errors changed during the 1970s, since there were more and different users who requested translations in different language combinations. Plus, the expectation of excellent quality from multilingual communities and international trade, made the MT industry rise in Europe, Canada, and Japan (Hutchins, 2015, p. 123).

3.2.4 The resurgence of AI (1980s)

During 1970s AI was an appreciated field to the research community, as the development of new systems and techniques, such as neural networks, provided new areas of research and practice. But the 1980s was quite different. The intention of creating new machines and the prediction of its usage ended. Intellectuals and AI researchers stopped focusing on the strong aspects of AI, such as the imitation of human cognitive abilities, and started to focus on the weak aspects of AI, which was the ability to solve specific problems (Jones, 2008, p. 10).

In 1981, Japan´s Ministry of International Trade and Industry (MITI) created an initiative called The Fifth Generation Computer Systems (FGCS), a 10-year plan aimed to build intelligent computers which can run Prolog, a logic programming language for AI. In response to this initiative, The U.S government created the Microelectronics & Computer Technology Corporation (MCC), a computer industry focused on research and development designed to assure competitiveness. Both of the initiatives were focused on AI, including chip design and human-interface design (Russell & Norvig, 2010, p. 24).

3.2.5 The discipline today (2000 - present)

During the decade of the 2000s, the use of MT increased in new areas such as television subtitles, localization, and social networking. Large scale use of MT also increased in global companies and translation services, which were mostly focused on the pre-processing of inputs and the post-editing outputs (Hutchins, 2015, pp. 133-134) as well as MT training.

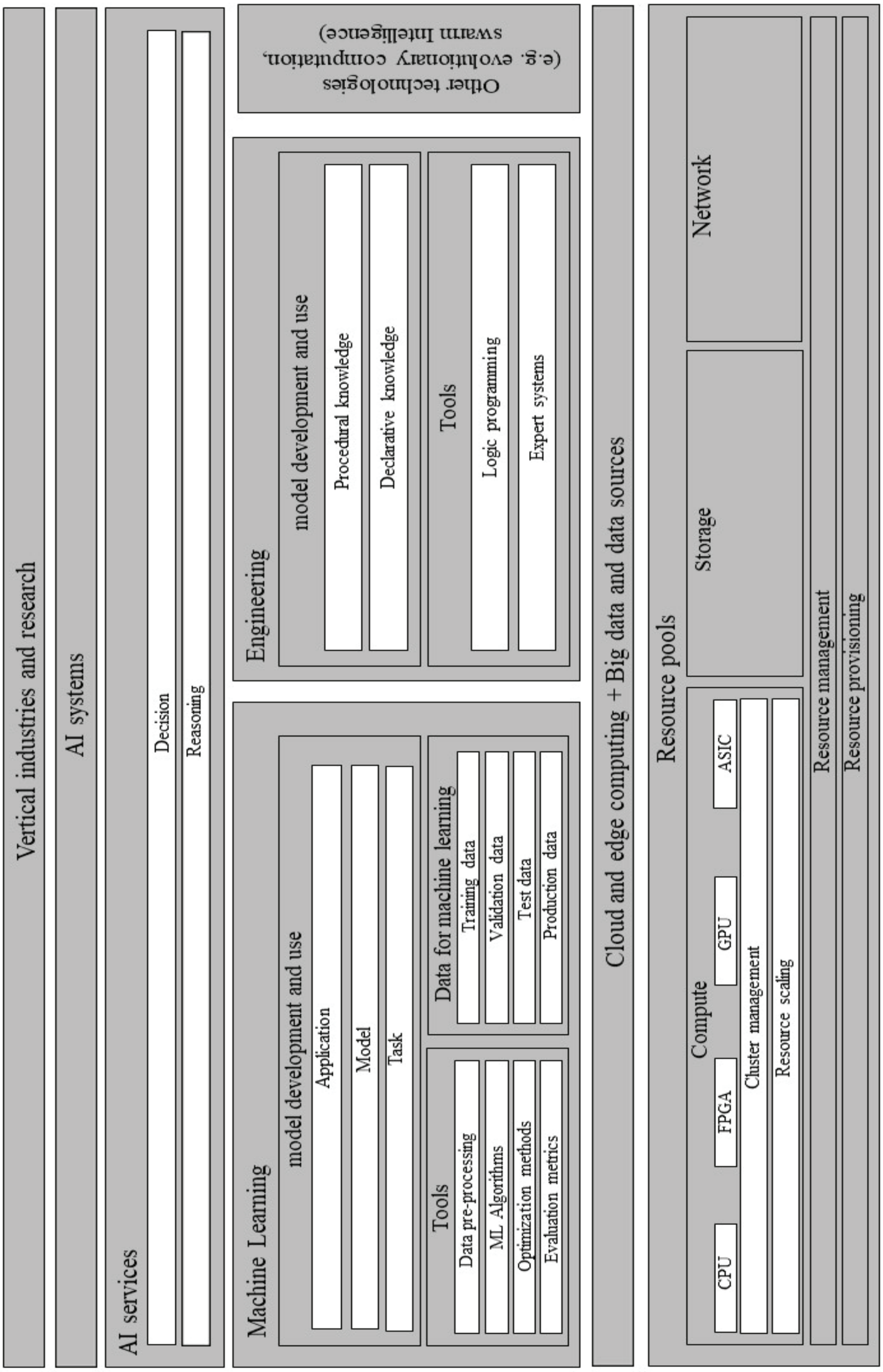
The first corpus used for data-driven MT was a corpus from the Canadian parliamentary proceedings, which were published in French and English. The European Union also published content in several of its official languages. In addition, the parliamentary acts were prepared as a parallel corpus in order to train MT systems. For the most spoken languages, such as French, Spanish, German, Russian and Chinese, there was plenty of data available. However, data scarce for the rest of the languages, especially for languages from so-called low-resource countries. Even in the case of widely spoken Asian languages, there is a great lack of available parallel corpora (Koehn, 2020 , p. 16).

The focus on MT in the translation market led to the decay of traditional translators as the more up-to-date translators were starting to use MT as helpful tools for their translations. These tools such as translation memories (TM), made translators save time and supplies them with the opportunity to provide high quality services. As for the clients and general public, the use of MT was no longer through software on PC Systems, but through online services such as Google Translate (Hutchins, 2015, pp. 120-136).

Years later, in 2015, AI made a remarkable comeback with the creation of AlphaGo, a Go computer program developed by DeepMind, which was later acquired by Google. The program was able to beat a professional player of the board game Go using a specific and more complex Artificial Neural Network (ANN) called Deep Learning (DL). A technical definition of ANN is given by Haykin (1999) stating that a neural network is "a massively parallel distributed processor made up of simple processing units that has a natural propensity for storing experimental knowledge and making it available for use." (p. 2). "ANNs are mostly used for universal function approximation in numerical paradigms because of their excellent properties of self-learning, adaptivity, fault tolerance, nonlinearity, and advancement in input to an output mapping." (Abiodun et al., 2018, p. 2). They are the basis of apps who belong to the AI field such as image recognition algorithms and self-driving cars, among others (Haenlein & Kaplan, 2019, p. 8).

Figure 1

AI ecosystem (ISO, 2021, 8)



According to ISO/CD 22989, AI is composed from various technologies, which can be used simultaneously. Figure 1 shows the structure of an AI ecosystem divided in functional layers. Each layer represented in gray uses the resources of the lower layers, represented in white, to perform an action. The varied sizes of the layers do not indicate that one layer is more relevant than other (ISO/CD 22989, 2021 , 8.1).

The definition of the most relevant components of AI to this document shown in figure 1 are:

1. AI systems: systems designed to create models that generate outputs through a reasoning process to achieve a desired goal through a decision process. In general, AI systems work by analyzing enormous amounts of training data and using the output of the analysis to make predictions. In AI there are several types of reasoning which include:

- Deductive reasoning: decides based on already known facts.
- Inductive reasoning: decides based on generalization with limited known facts.
- Abductive reasoning: decides based on observations that help find the most suited explanation for the observation.
- Common sense reasoning: decides based on experience (ProfessionalAI, 2020).

Translation and interpreting AI systems, such as MT, use deductive reasoning as they were trained before to obtain the vocabulary and grammar patterns of a language. For example, in a translation from English to Spanish using the most recent MT systems, the text you insert goes through a decision process where the machine tries to provide the most accurate translation among all the viable options.

2. AI services: once the AI system-generated model is finished, AI services "compute a prediction, a classification or more generally a decision that would help to reach the current goal of an AI system."
3. Machine Learning (ML): the field of AI concerned on developing mechanisms to make a machine learn through experience and training.
4. Engineering: includes expert systems and logic programming. Expert systems are AI systems concerned on saving specialized knowledge a human has provided to later generate outputs that solve problems. Logic programming is defined as "a form of programming based on programming languages that express formal logic."

Formal logic constitutes a crucial part of the AI research since its purpose is the creation of models of human reasoning.

5. Cloud and edge computing, big data, and data sources: big data can be defined as large and complex datasets which require a specialized technology for data processing to be able to manage it. The data can come from a wide variety of sources such as research organizations, surveys, or images.

   Cloud computing is a paradigm that enables storing and access to data. Likewise, edge computing is defined as “distributed computing in which processing, and data storage takes place at or near the edge of the network where the nearness is defined by the system requirements.”
6. Resource pools: resources such as compute, network and storage that support the AI ecosystem (ISO/CD 22989, 2021, 8).

AI has come a long way from McCulloch and Pitts to McCarthy and Minsky, from the *Turing Test* to the conversational intelligent agents. The ideas, concepts, machines, and human development have been remarkably close to make the conceptual step from seeing intelligence as exclusive to humans, to thinking about building intelligent and useful entities. The theoretical and practical study of intelligent systems has led to AI being an experimental science. In its laboratories the central instrument is a computer; in which most of the results of its research are computer programs, written in programming languages, so that the computer is able to understand and execute the programmed instructions. It is a science field that has not ceased to grow faster and faster with greater impact during the present days (Trillas, 1998, p. 63).

3.3 State of the art

The main goal of the study and development of AI is to build systems capable of performing tasks that normally require a certain degree of human intelligence. AI-powered machines are able to be adaptive, perceive certain environments, and use techniques acquired from many fields, such as computer science, mathematics, philosophy, and linguistics to perform different tasks. An example of interaction with the environment is the object recognition feature (ISO/CD 22989, 2021, 5.1).

The growth of high technology over the years has led AI being useful not only in different professional areas, such as translation and interpreting, but in everyday life tasks. One of the most famous examples of AI in daily tasks is the iRobot Corporation, which has sold millions of Roomba robotic intelligent vacuum cleaners for home use. Another example is the robotic vehicles, such as the driverless car named STANLEY. This Volkswagen car is equipped with cameras, radar, and laser rangefinders to sense the environment, plus a software to command the steering, braking, and acceleration, which can see traffic rules, avoid pedestrians and other vehicles (Thrun, 2006, pp. 664-668). Examples of success are the reason large companies, looking for innovation, are heavily investing in areas such as mechanized text, chatbots and automated information retrieval. In recent years, more advances in the AI field such as AI-powdered intelligent agents, virtual assistants, and MT tools such as Google Translate, and DeepL Translator, are also among the most famous and visible success of the field.

Another example of the potential of AI is ASR. ISO/CD 22989 defines ASR as “the conversion of a functional unit from a speech signal to a representation of the content of the speech.” (ISO, 2021 , 3.5.17). An example of the usage of ASR is the online translator Papago, created by the Korean company Naver. Papago allows a conversation to be held using ASR to generate an immediate translation. Papago, as Google Translate, has the possibility of listening to the translation, which can practically become an interpreter. Advanced MT tools as Papago, have the downside of not being able to process a completely fluent conversation between humans. Conversation and language generation run differently depending on aspects such as culture, the formality degree, and the tone of the voice. ASR tools continue to have problems with accents, dialects, idioms, unclear speech, and the fact that a small misunderstanding can change the course of an interaction, which can even result in the opposite of the expected outcome (Lommel, 2019 , p. 31).

The topic of translation technology continuously shows up in global conferences and educational institutes, which is now is turning out to be increasingly well known. In recent years, technology giants such as Tencent, iFLYTEK and Baidu have entered the field of AI-powdered translation with the creation of translation software as the Xiaoyi translator, which has excellent translation outcomes and speed. High technology translation software can provide constant, exact, and quick translations for different language combination in order to surpass the hardships brought by language barriers (Zheng, & Zhu, 2020, pp. 2-3).

AI-powered translation technology is not only suited for the translation industry, but also brings innovative approaches to the interpreting industry. During difficult topic interpretations, such as medical conferences or the interpreting of a trial, the interpreter may miss an important sentence or lack the translation of unexpected terms, reason MT, for example, is an excellent tool to prevent and help the interpreter in these unexpected situations (Zheng & Zhu, 2020 , p. 3).

3.4 Natural language processing

Natural language processing (NLP) is "the subfield of computer science concerned with using computational techniques to learn, understand, and produce human language content." (Hirschberg & Manning, 2015, p. 261). A Natural language is a language used by humans for writing and speech communication (Chopra et al., 2013, p. 131). However, ISO/CD 22989 provides a simpler definition stating that NLP is a "discipline concerned with the way computers process natural language data." (ISO, 2021 , 3.5.10).

NLP is based on two main components:

1. Natural language understanding (NLU): defined by ISO/CD 22989 as "the extraction of information, by a functional unit, from text or speech communicated to it in a natural language, and the production of a description for both the given text or speech, and what it represents."
2. Natural language generation (NLG): defined as the process of transforming data into natural language (ISO, 2021, 3.5.11).

Figure 2

Natural language processing (Chopra, et al., 2013, p. 131)

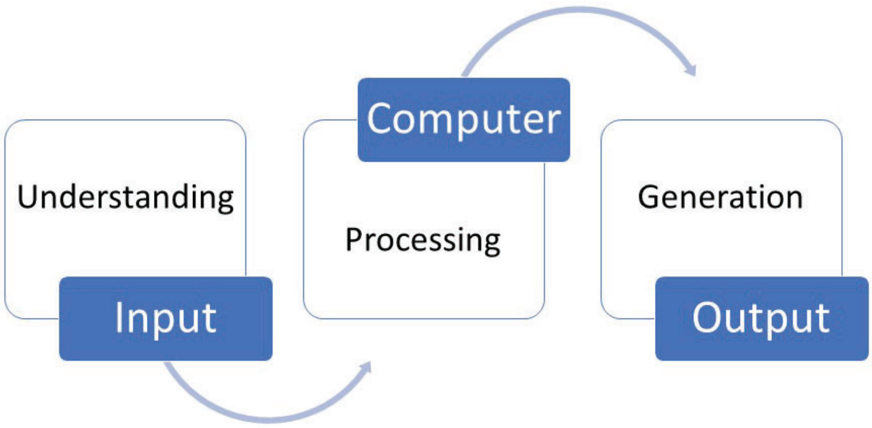


Figure 2 illustrates the process that natural language follows when processed by a computational system. First, an input is introduced into the system, which the NLU system will identify and understand. Once identified, the computational system will process it to generate an output with the NLG system.

Liddy gives a more detailed definition of what NLP is, stating that it is "a theoretically motivated range of computational techniques for analyzing and representing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications." (2001, pp. 2136-2137). By using NLP, a computer can analyze human-produced natural language texts and learn by finding the inner human aspects, such as the emotions, relations, and concepts to be able to produce text or speech (ISO/CD 22989, 2021, 9.2.1).

Computational language systems are designed to serve different purposes:

1. Human-to-human communication, as in MT.

2. Human-to-machine communication, as in conversational agents.

3. Analyze and learn from large quantity of human language content (Hirschberg & Manning, 2015, p. 261).

Applications of NLP are widely found in today's companies, due to the enormous amount of data they have to analyze. This makes NLP to be an increasingly relevant discipline for companies. NLP applications include market intelligence, survey analysis and sentiment analysis. Companies need to understand their clients as well as their feelings to be able to create specific strategies and evaluate their results. Companies should also be able to control and evaluate their performance by getting feedback from their customers, as well as having the chance to improve based on customer-liking. To sell their products and services, companies also need to create targeted advertisements. NLP is an ideal tool for keyword analysis and browsing patters on the internet, social media, and mail to place the optimal advertisement in the right moment at the right place.

NLP has also applications in the hiring and recruiting process since it allows the HR team to extract relevant information about candidates such as educational background, experience, name, and location to provide the company with the perfect candidate. Text summarization is also a particularly important task for a company, since it needs to have the most relevant information instead of large amount of data. NLP is able to extract the most relevant information and summarize it in two ways:

1. Extraction-based summarization: extract key phrases and create a summary with the information already provided.
2. Abstraction-based summarization: paraphrase the information to create a summary with added information.

More NLP applications include tasks such as ASR, copywriting, and e-mail spam detecting. ASR is mostly used in the virtual assistants, such as Cortana and Siri, which are able to understand commands and perform them with high quality.

For translators and interpreters, NLP techniques such as grammar checkers are especially important since they are extremely useful tool to provide quality and save time. However, to professional translators and interpreters, neural machine translation (NMT) is the most relevant application of NLP, since it is deeply connected to the profession. NMT is one of the oldest applications of NLP, but it is still important to companies and freelancers (Great Learning Team, 2021).

According to Koehn, NLP still encounters problems of ambiguity on every level when translating. NLP has problems with homonyms, morphosyntax, and the relationships with distinct aspects of the text. Humans, unlike today's machines, are able to manage and understand ambiguity thanks to context and experience. However, misunderstandings are possible, as there are occasions where the sender is ambiguous on purpose in order to not commit to a particular interpretation. In this particular case, the translator has to maintain the ambiguity, as it is part of the internal meaning of the text (2020, pp. 5-8).

3.5 AI in translation and interpreting

Machine learning algorithms have been designed to manage substantial amounts of data, which can come in structured or unstructured, as it is necessary for testing purposes (ISO/CD 22989, 2021, 5.9). Machine learning (ML) is a subfield of AI which is based in the process of learning from experience (Jones, 2008, p. 16). However, a more accurate definition of ML is provided by ISO/CD 22989 stating that ML is “a process using computational techniques to enable systems to learn from data experience.” (ISO, 2021, 8.4.2). An agent is said to have learned when it improves its performance on future tasks by building on what it has learned from previous tasks. According to Russell and Norvig (2010) there are two main reasons why it is useful for a machine to learn rather than to be programmed: first, designers cannot foresee all possible situations in which the agent may find itself or anticipate all the changes over time; a program designed to predict tomorrow's stock market prices must learn to adapt to situations in constant change.

Second, there are times when human programmers do not know how to program a solution for a problem. An example of this case would be facial recognition: most people are good at recognizing the faces of their family members, but even programmers are unable to program a computer to perform that task, except by developing learning algorithms which are able to learn how to do it. ML consists of a set of four methods: supervised learning, semi-supervised learning, unsupervised learning, and probabilistic approaches.

1. Supervised learning: this method requires external assistance to decide whether the responses given are valid or invalid. The input data contains a predictor, which is the independent variable, and a target, which is the dependent variable. The value of both variables is estimated in advance. Through the process of supervised learning, the algorithm predicts the value of the dependent variable based on the independent variable. An example of supervised learning is the decision tree, which represents different choices, as well as their potential results in form of a tree (p. 693).
2. Unsupervised learning: this approach does not require a teacher's judgment to validate the answers, as it learns from the data. In this case, there is no target available, but relationships in the data that are used for classification (Jones, 2008, p. 16). The most common unsupervised learning task is clustering, which is detecting potentially useful groups of input examples (Russell & Norvig, 2010, pp. 694-695).
3. Semi-supervised learning: a learning method based on a combination of supervised and unsupervised learning. A well-known example of the semi-supervised learning is self-training. According to Mahesh “in self-training, a classifier is trained with a portion of labeled data. The classifier is then fed with unlabeled data. The unlabeled points and the predicted labels are added together in the training set. This procedure is then repeated further.” (2020, p. 384).
4. Reinforcement learning: The agent is able to learn from a reward or punishment (Russell & Norvig, 2010, p. 695). An example of the reinforcement learning applications is the learning-based robots designed to provide efficiency in the industry sector, as well as do dangerous tasks for humans (Mahesh, 2020, p. 384).

ISO/CD 22989 adds one more ML method:

5. Transfer learning: Consists of transferring a set of methods previously designed for a model that was created to solve one problem to another model designed to solve a different problem. An example is the algorithm created to identify house numbers in a street view used to recognize handwritten numbers (ISO, 2021, 5.10.5).

In the present day, with the help of ML, MT and other AI-powered tools, the process of creating a translation becomes different in comparison to the traditional translation process. Even though there is the possibility of finding errors performed by MT, there are still two main points that makes the modern world still invest on its development. The first one comes from a scientific approach, which focuses on the complexity of a computer-simulated human translation. Translation is a linguistic activity; it goes from acknowledgment of graphemes (and phonemes in interpreting) to the transmission of the meaning in a written and oral text, which makes the discipline, along with the characteristic feature of translation in general and MT, considered to be an interesting field for the AI research community. The second point comes from a social perspective. To be able to solve problems derived from communication between languages, there is no alternative to translation. It is relevant to keep investing and continue to create tools that helps translators and assure the highest quality possible for a translation (Altynbekova, 2020, p. 2). The presence of AI is, for translators and interpreters, an important development for their possibilities.

Along with AI-powered translation tools, CAT tools are highly demanded in the translation industry. A peculiarity of CAT tools is that considers the translator to be the center of the translation process, conceiving MT only as a helper. Kastberg & Andersson offer a distinction between translation methods based on two aspects: the degree of automation presented in the translation tool and the controller of the decision-making process during the translation (2012, pp. 34-45):

1. Human translation: the translation is made 100% by a human translator with no use of MT or CAT.
2. Fully automated MT (FAMT): the translation is made 100% by MT with no interaction of a human translator.

3. Human-aided MT (HAMT): the translation is made entirely by the MT with the help of a human translator just for the pre-editing and post-editing process.
4. Machine-aided human translation (MAHT): the human translator is the main protagonist of the translation process, while the MT and CAT are used only as a tool.

Because of its minimal expense and high proficiency working structure, AI translation technology innovation has step by step becoming appreciated for translators. Along with the improvement of AI, CAT innovation has made extraordinary accomplishments, as the introduction of AI applications to translation and interpreting industry have significantly lowered the work and intensity of the translation process (Zheng & Zhu, 2020, p. 2). However, AI-powered translation tools, such as MT, should not be confused with CAT, as the latter does not translate by itself and merely assist the translator in the process, whereas MT does translate by itself. It would be optimal if translators did not just utilize already translated texts, provided by Translation Memories (TM), but additionally have new MT instruments that can assist them in creating new segments not available in the TM (Zaretskaya et al., 2015 , p. 76).

3.6 Machine translation

MT is an NLP task used to translate a text from one natural language to another (ISO/CD 22989, 2021, 3.5.5). However, most of the tools only operate with English and some European languages, which makes it available to a limited population. MT has had several points of view and research approaches that have been studied through decades. Chéragui, for example, divided the MT approaches in two groups: Computational Architectures and Linguistic Architecture of MT (2012, pp. 163-164). However, authors such as Hutchins (2015) and Tripathi and Sarkhel (2010) provide similar contributions with no distinctions of architecture.

According to Tripathi and Sarkhel, there are four MT approaches (2010, p. 389):

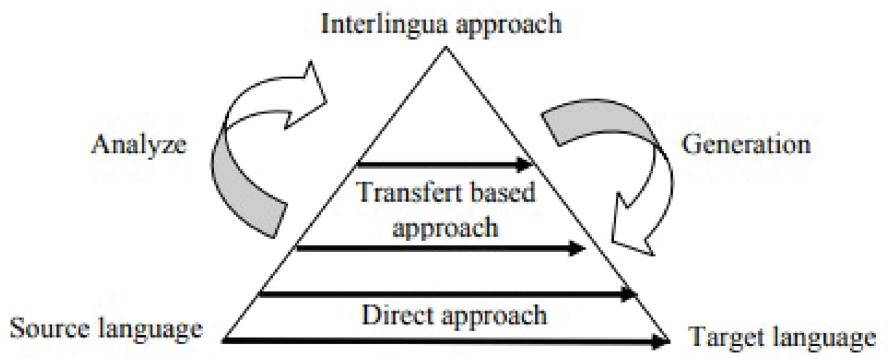
1. Dictionary-based MT (DBMT)

   This approach involves the creation of translations by searching for linguistic equivalents in language dictionaries without a context.
2. Rule-based MT (RBMT)

RBMT systems transform source language (SL) linguistic structures to target language (TL) equivalents. Inside RBMT there are different approaches and the Vauquois triangle shown in figure 3 illustrates those three types of RBMT approaches:

Figure 3

Vauquois' triangle (Liu & Zhang, 2015, pp. 110)



1) Direct approach: based in a set of rules to translate the SL to a TL using minimum analysis and syntactic reorganization.
2) Interlingua approach: based on translating abstract representations of language, by first translating the SL to the interlingua and the interlingua to the TL.
3) Transfer-based approach: focused on the abstract part of the text to obtain the meaning of the SL to later translate it into an equivalent TL representation (Hutchins, 2015, p. 120).

3. Knowledge-based MT (KBMT)

   KBMT is based on RBMT. However, the main difference is that KBMT focuses on the understanding of both the SL and TL (Tripathi & Sarkhel, 2010, p. 390).

4. Corpus-based MT

   It is based on the use of bilingual stored data or corpus to create the translations (Chéragui, 2012, p. 165). Some of the approaches are:

   1) Statistical MT (SMT): statistical methods and a large amount of linguistic data, are used to generate the final translation.
   2) Example-based MT (EBMT)

      Based on the search of equivalent fragments within the language combination. It is also known as Memory-based translation.

3) Context-based MT (CBMT)

   Similar to the Corpus-based approach. To translate, CBMT only requires a large monolingual corpus related to the target text, a bilingual dictionary, and a smaller monolingual corpus related to the source text (Tripathi & Sarkhel, 2010, p. 391).

However, Chéragui includes one more approach:

5. Hybrid approach MT

   It is the combination of the transfer approach discussed in the RBMT and CBMT. The idea is to reduce the need of excessive amounts of resources and depend on the learning capacity of the transfer rules (2012, p. 165).

The performance process of MT should also be addressed to understand its importance. It consists of three parts: a translation model, a language model, and a decoder. A translation model is made out of a list containing possible translations of each word and sentence of the original text with the frequency of occurrence for each possible translation. The system contains millions of translations of words and phrases for each linguistic combination and is able to compare both single words and phrases of several words. The language model is created by the system during the first phase of text analysis and the decoder makes the translation. The decoder performs a morphological and syntactic analysis of the text and ranks all the translation options in descending order of probability for each sentence, in order to later select the most accurate combination of probability and frequency (Altynbekova, 2020, p. 6).

AI-powered technology tools are having an impact in both the translation and interpreting industry. Most of the AI-powered translation tools are also useful and have almost the same impact in the interpreting industry as they do in translation. However, it is important to distinguish the diverse types of interpreting technology, which include:

1. Distance interpreting: technology used to provide interpreting services to clients who are not in the same place as the interpreter.
2. Technology-supported interpreting: the use of technological tools, such as digital pens and tablets to support the interpreting process. Includes Computer-assisted Interpreting (CAI) tools.
3. Machine Interpreting (MI): technologies created to support human interpreters. They are a combination of ASR and MT systems. However, it can also be added

TTS systems, which is the technology that converts digital written text into speech, and speech synthesis tools (Braun, 2020, p. 274).

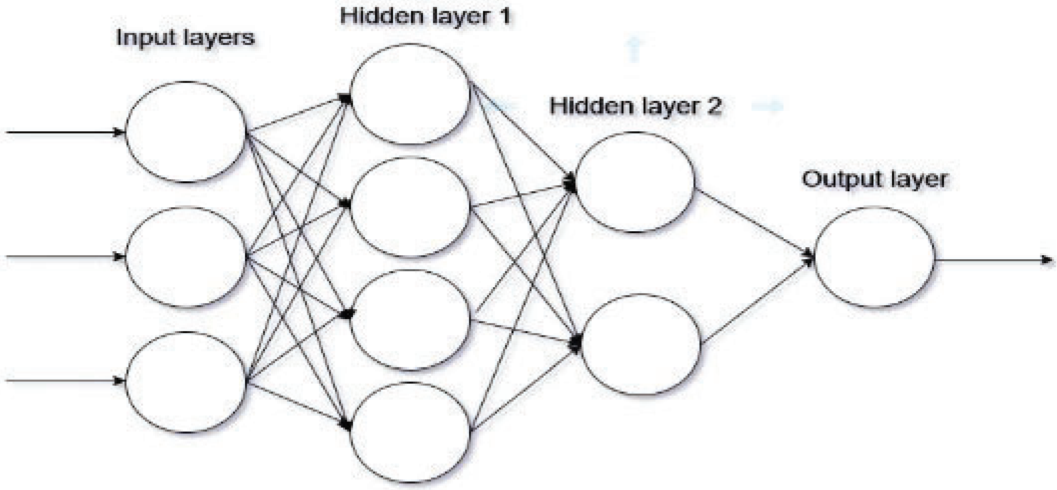
Now that the MT and MI are introduced, it is also pertinent to address more in depth some of the approaches of MT relevant to this document, which are ANN and Neural Machine Translation (NMT). NMT is "the use of a neural network to translate minimal impact content and speed up communication with its partners. A bidirectional recurrent network called an encoder processes a source sentence into vectors for another recurrent neural network, called the decoder." (Great Learning Team, 2021).

Mahesh states that an ANN is "a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates." (2020, p. 385). However, a more precise definition of ANN is given by ISO/CD 22989 stating that an ANN is "a network with two or more layers of neurons connected by weighted links with adjustable weights, which takes input data and produces outputs." (ISO, 2021, 3.3.7). ANN performance model how the human brain works, since is based on human brain neurons and is able to develop capabilities such as observe, learn, and solve problems.

In ANN systems, the neurons get trained to learn by themselves how to solve specific problems, which is done by processing carefully selected examples and providing the computer with data to determine valid analysis criteria (Maind & Wankar, 2014, pp. 96-97). They learn with known inputs by comparing the actual result with the expected one using weights and errors. ANN are coordinated in layers, where the result of one layer turns into the contribution to the following layer and every neuron gets inputs to produce one output. Different weight is assigned to the connection through a supervised or unsupervised learning algorithm depending on the importance of the input. The stronger connections get stronger and the weak connections, which are the ones that generate incorrect solutions to a problem, get weaker (ISO/CD 22989, 2021, 5.11.2.1). The input layer receives a command, and the output layer produces a result. Usually, there are one or more hidden layers between the two main layers. However, there are also models of ANN without hidden layers. According to Maind and Wankar, most applications require networks with a minimum of the three normal types of layers: input layer, hidden layer, and output layer (2014, p. 98). Figure 4 shows the connections of a neural network with an input layer, two hidden layers, and an output layer.

Figure 4

Artificial Neural Network layers (Jha et al., 2016, p. 1494)



Neural networks are the base for most of ML algorithms. Those algorithms are the roots of the highest impact approach of MT, which is the NMT. NMT instruments are significant tools for translators, since they can translate vast number of words with an even more sensible quality than standard MT systems (Bahdanau et al., 2015).

4. Conclusions

AI technology continues to grow exponentially with the support of large companies. Successful outcomes in AI have led the field to show up in global conferences and become relevant in a wide range of disciplines, including translation and interpreting. To deal with AI technology, translators and interpreters need to learn and thus remain in the industry with knowledge that is valued both for companies and for their own career. However, professionals still value having other skills related to translation to ensure creativity and originality, which AI-powered tools are still unable to provide.

The implementation of MT, NLP, and every other approach of AI technology applied to translation and interpreting has led to an era where sound knowledge of a wide variety of languages is no longer considered an exceptional skill. Chopra et al. (2013) state that NLU will provide computers and machines the ability to learn and apply the knowledge to real life situations. In combination with AI-approaches, computers and machines will become more fluent in receiving and providing useful information (p. 133).

MT contains hundreds of language combinations and translators have their knowledge limited to only a few. Even though the importance of being fluent in various languages has declined because of MT, translation and communication remain important. Translation tasks in specific fields such as advertising, where content has to be recreated very often, or in constant changing fields such as legal, will always require human knowledge and creativity, reason translation and interpreting should be a teamwork between machines and humans (Schmidt, 2020). A standard-quality translation requires not just the capacity to breakdown and create sentences in a natural language but also a humanlike comprehension of the world, context, and the ambiguities of languages, as it is an impossible task for a machine to do by itself (Hirschberg & Manning, 2015, p. 261).

Professional translators and interpreters are fully aware that machines make mistakes, just as humans do. However, human translators have more information regarding the assignment and the context of the translation. This is where the biggest difference between the MT and human translator lies, and it is crucial for the human translator to be aware and guide their translation career to take advantage of this crescent niche.

Due to the high-dependence and well performance of the AI-powered online translation tools, such as grammar checkers, ASR, and MT, professional translators fear that their job can be replaced and become redundant in some aspects of translation, such as the PE process, which can lead to the increase of insecurities among professionals. Translators and interpreters have far more to offer than language-related competence. Professionals should start seeing themselves as language specialists with a useful set of knowledge, skills, and experience and be aware of the mistakes AI-powered online translation tools can make as well as its low points. However, qualified translators and interpreters are also aware of the advantages technology is providing, which continue to challenge professionals to develop creativity and extended knowledge to assure their present and future career (Grizzo, 2019, pp. 34-35). Here is an explanation of the advantages and disadvantages of the use of AI-powered online translation tools:

Advantages:

1. Tools such as grammar checkers and ASR save time, provide a higher quality, and prevent future mistakes.
2. There is a wide variety of language combinations available online in different MT platforms, which expands the translators' possibilities.

3. There are multiple AI-powered translation tools available online for free, such as text summarization tools, virtual assistants, and paraphrasing tools.

Disadvantages:

1. Lack of context. This problem would make a MT-generated translation difficult to understand and not reach the expected quality.
2. Lexical polysemy. Different meanings and stigmas attached to words appear in diverse cultures and languages, which in addition to the lack of context, can outcome fatal errors in translation.
3. Lack of in-depth knowledge of languages. AI-powered online translation tools offer a wide variety of language combinations, but still can make costly errors. A human translator specialized in language combination would bring a safer and richer translation.
4. Lack of creativity (Altynbekova, 2020, pp. 17-18).

The research on AI is driven by the human need to create solutions to problems that require a certain degree of human intelligence. It is estimated that AI growth will be accompanied by disciplines such as big data, the improvement of graphics processing units (GPUs) and the development of DL. Experts foresee that investing in the research of DL is the opportunity for the development of Deep Reasoning (DR). DR is the analogy of what DL has come to achieve in terms of perception and classification but in the realm of reasoning. However, DL is still in the process of demonstrating its full potential by working with "small data" and new hardware in order to provide knowledge to fully develop DR, which it is still on its early days. AI technologists expect this happening in 5 to 10 years along with more use of unsupervised learning, as it is necessary to improve the machine learning process in order to propose innovative solutions to increasingly complicated problems (IBM, 2016).

As for the translation and interpreting industry, AI-powered translation still has major limitations and human translators are still needed in the translation process, as human translator knowledge is still needed to assist MT. However, improvements in NMT are undeniable when making a comparison with old translation tools. According to Zong and Hong "With the continuous development of artificial intelligence technology, new technologies for natural language processing will change the industrial construction of translation, and the translation industry chain may experience a major industrial change."

(2018, p. 510). Successful advances will continue to change the industry as technology develops, and those translators and interpreters who adapt to change will be the ones who succeed.

5. Bibliography

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon*, *4*(11). https://doi.org/10.1016/j.heliyon.2018.e00938. Last access October 24th, 2022.

Altynbekova, L. (2020). *ARTIFICIAL INTELLIGENCE AND TRANSLATION TECHNOLOGY* [Master´s thesis, Kazguu University] http://repository.kazguu.kz/handle/123456789/973. Last access October 24th, 2022.

Bahdanau, D., Cho, K., & Bengio, Y. (2015, May 7-9). *Neural Machine Translation by Jointly Learning to Align and Translate* [Conference oral presentation] ICLR 2015, San Diego, CA, United States. https://arxiv.org/abs/1409.0473.

Braun, S. (2020). Technology and Interpreting. In O'Hagan, M. (ed.), *The Routledge Handbook of Translation and technology* (pp. 271-288). Routledge.

Chéragui, M. A. (2012). Theoretical Overview of Machine translation. *Proceedings of the 4th International Conference on Web and Information Technologies, Algeria, 867,* (pp. 160-169). http://ceur-ws.org/Vol-867/Paper17.pdf. Last access October 24th, 2022.

Chopra, A., Prashar, A., & Sain, C. (2013). Natural Language Processing. *International Journal of Technology Enhancements and Emerging Engineering Research*, *1*(4), 131-134. https://issuu.com/ijteee/docs/natural-language-processing. Last access October 24th, 2022.

Dean, T., Allen, J., & Aloimonos, Y. (1995). *Artificial Intelligence: Theory and Practice* (1st ed.). Addison-Wesley.

Dennett, D. C. (1988). When Philosophers Encounter Artificial Intelligence. *Daedalus*, *117*(1), 283–295. http://www.jstor.org/stable/20025148. Last access October 24th, 2022.

Descartes, R. (2006). *A Discourse on the Method* (I. Maclean, Trans.). Oxford University Press. (Original work published 1637).

Great Learning Team. (2021, December 31). 11 Trending Natural Language Processing Applications in 2022. *Great Learning*. https://www.mygreatlearning.com/blog/trending-natural-language-processing-applications/. Last access October 24th, 2022.

Grizzo, S. (2019). The challenge of being a translator – and a client – in the age of AI. *tcworld, November 2019*, 33-35.

Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925. Last access October 24th, 2022.

Haykin, S. (1999). *Neural networks and learning machines* (3rd ed.). Pearson Education.

Hirschberg, J., & Manning, C. D. (2015). Advances in natural language processing. *Science*, *349*(6245), 261-266. https://www.science.org/doi/abs/10.1126/science.aaa8685. Last access October 24th, 2022.

Hutchins, J. W. (2015). Machine translation: History of Research and Applications. Chan, S.-W. (Ed.), *Routledge Encyclopedia of Translation Technology* (1st ed., pp. 120-136). Routledge.

IBM. (2016). *The new AI innovation equation*. https://www.ibm.com/watson/advantage-reports/future-of-artificial-intelligence/ai-innovation-equation.html. Last access October 24th, 2022.

International Organization for Standardization. (2021). Information technology — Artificial intelligence — Artificial intelligence concepts and terminology (ISO Standard No. CD 22989:2021).

Jha, K., Doshi, A. & Patel, P. (2016). Artificial neural network layers [jpg]. International Journal of Advanced Research. International Journal of Advanced Research, 6(Oct), 1493-1502. http://dx.doi.org/10.21474/IJAR01/7959. Last access October 24th, 2022.

Jones, T. M. (2008). *Artificial Intelligence: A Systems Approach.* Jones & Bartlett Learning.

Kastberg, P., & Andersson, T. B. (2012). Machine Translation Tools-Tools of the Translator's Trade. *Communication & Language at work*, *1*(1), 34-45. https://tidsskrift.dk/claw/article/download/7238/6172. Last access October 24th, 2022.

Koehn, P. (2020). *Neural machine translation*. Cambridge University Press.

Liddy, E. D. (2001). Natural language processing. In M.A. Drake (ed.), *Encyclopedia of Library and Information Science* (3rd ed., pp. 2126-2136). Marcel Dekker, Inc.

Liu, Q. & Zhang X. (2015). Vauquois' triangle [jpg]. R*utledge Encyclopedia of Translation Technology* (1st ed., pp. 105-119). Routledge.

Lommel, A. (2019). Beyond translation: Conversational content in a multilingual world. *tcworld, November 2019*, 30-32.

Lu, Y. (2019). Artificial intelligence: a survey on evolution, models, applications and future trends. *Journal of Management Analytics*, *6*(1), 1-29. https://www.tandfonline.com/doi/pdf/10.1080/23270012.2019.1570365?needAccess=true. Last access October 24th, 2022.

Mahesh, B. (2020). Machine Learning Algorithms - A Review. *International Journal of Science and Research (IJSR), 9*(1), 381-386. https://www.ijsr.net/get_abstract.php?paper_id=ART20203995. Last access October 24th, 2022.

Maind, S. B., & Wankar, P. (2014). Research Paper on Basic of Artificial Neural Network. *International Journal on Recent and Innovation Trends in Computing and Communication*, *2*(1), 96-100. https://ijritcc.org/index.php/ijritcc/article/download/2920/2920/2895. Last access October 24th, 2022.

Poole, D. L., & Mackworth, A. K. (2010). *Artificial Intelligence: Foundations of Computational Agents.* Cambridge University Press.

ProfessionalAI. (2020, June 16). Reasoning in Artificial Intelligence. *ProfessionalAI.com*. https://www.professional-ai.com/reasoning-in-artificial-intelligence.html. Last access October 24th, 2022.

Russell, S. J., & Norvig, P. (2010). *Artificial Intelligence A Modern Approach* (3rd ed.). Prentice Hall.

Schmidt, J. (2020). What can linguistic AI do for you today – and tomorrow? *tcworld, February 2020*, 22-25.

Tanimoto, S. L. (1990). *The Elements of Artificial Intelligence Using Common LISP* (Principles of Computer Science Series). Computer Science Press.

Thrun, S. (2006). Stanley: The Robot that Won the DARPA Grand Challenge. *Journal of Field Robotics, 23*(9), 661–692. https://onlinelibrary.wiley.com/doi/epdf/10.1002/rob.20147. Last access October 24th, 2022.

Trillas, E. (1998). *LA INTELIGENCIA ARTIFICIAL. MÁQUINAS Y PERSONAS* (1st ed.). Editorial Debate.

Tripathi, S., & Sarkhel, J. K. (2010). Approaches to machine translation. *Annals of Library and Information Studies, 57*(4), 388-393. http://nopr.niscpr.res.in/handle/123456789/11057. Last access October 24th, 2022.

Turing, A. M. (1950). Computing Machinery and Intelligence. *Mind*, *LIX* (236), 433-460). http://www.jstor.org/stable/2251299. Last access October 24th, 2022.

Vauquois, B. (1968). A survey of formal grammars and algorithms for recognition and transformation in mechanical translation. In Ifip congress (2) (Vol. 68, pp.1114-1122).

Zaretskaya, A., Pastor, G. C., & Seghiri, M. (2015). Integration of Machine Translation in CAT tools: State of the art, evaluation, and user attitudes. *SKASE Journal of Translation and Interpretation*, *8*(1), 76-88. http://www.skase.sk/Volumes/JTI09/pdf_doc/04.pdf. Last access October 24th, 2022.

Zheng, S., & Zhu, S. (2020). A Study of Computer Aided Translation Based on Artificial Intelligence Technology. *Journal of Physics: Conference Series, China, 1646*(012127). https://doi.org/10.1088/1742-6596/1646/1/012127. Last access October 24th, 2022.

Zong, Z., & Hong, C. (2018). On Application of Natural Language Processing in Machine Translation. *2018 3rd International Conference on Mechanical, Control and Computer Engineering (ICMCCE)*, (pp. 506-510). https://ieeexplore.ieee.org/document/8537610. Last access October 24th, 2022.

Affidavit

I, Carla Hidalgo de Torralba Padrón with DNI/NIE 45169862R, student of the official degree "English-German Translation and Interpreting" of the Faculty of Translation and Interpreting of the University of Las Palmas de Gran Canaria, academic year 2022 - 2023, and as author(s) of this academic document, entitled:

Artificial Intelligence in Translation and Interpreting

and presented as a final thesis, for the award of the corresponding degree,

DECLARE THAT

it is the result of my personal work, that I do not copy, that I do not use ideas, formulations, integral quotations and diverse illustrations, taken from any work, article, memory, etc., (in printed or electronic version), without clearly and strictly mentioning their origin, both in the body of the text and in the bibliography. I am also fully aware that failure to respect these extremes is subject to university and/or other sanctions.

Signature: HIDALGO DE TORRALBA PADRON CARLA - 45169862R

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In Las Palmas de Gran Canaria, October 26th, 2022.