

Quantum Mechanics for Language Understanding and Generation

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Abstract

The project “QUantum Mechanics for LAnguage Understanding and gEneration” (QUMLAUDE) investigates how quantum information representation and algorithms can be successfully integrated into Natural Language Processing (NLP) tasks and applications. By leveraging quantum-inspired algorithms, we aim to model nuanced linguistic phenomena with special attention to semantic representation (e.g., semantic composition) where quantum advancements promise to deliver more accurate and precise results compared to current methods. QUMLAUDE has a duration of 3 years and has been organised into six modules: Quantum representation of the text (M1); Quantum and Quantum-inspired Algorithms for NLP (M2); Integrating quantum theory in NLP tasks and applications (M3); Use Case: Retrieval Augmented Generation system for the innovation domain (M4); Dissemination (M5) and project management (M6). Bringing together a multidisciplinary and diverse team of experts, the research conducted in this project will not only deepen the understanding of quantum-enhanced NLP but also foster new standards in quantum computing applications.

Keywords

Natural Language Processing, Quantum Mechanics, Quantum Computing, Quantum Machine Learning

1. Introduction and Motivation

“QUantum Mechanics for LAnguage Understanding and gEneration” (QUMLAUDE)¹ is a cutting-edge research project funded by the Spanish Ministry of Science, Universities and Innovation, which is conducted by a team of 15 multi-disciplinary researchers (senior, post-docs and PhDs) belonging to the GPLSI² group of the University of Alicante.

The motivation behind this project stems from the exploration of quantum mechanics principles in the field of Artificial Intelligence [1], and more specifically to NLP, which are emerging research areas increasingly gaining international recognition and momentum across both academia and industry. In classical computing, Boolean algebra is used, so information is represented using bits (0, 1), whereas quantum computing, the unit employed is a qubit, with two main key properties: i) superposition, i.e., each qubit can adopt 0 and 1 superposed; and ii) entanglement, which means that allows qubits separated by incredible distances to interact instantaneously with each other and retain a type of connection, forming pairs, through a correlation process. The combination of the phenomena of quantum superposition and quantum entanglement makes it possible to multiply the processing capacity exponentially. While a 2-bit register in a normal computer is only capable of storing one of the four binary configurations (00, 01, 10 or 11), a 2-bit register in a quantum computer can store all four numbers

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¹<https://qumlaude.gplsi.es/es/inicio/>

²<https://gplsi.dlsi.ua.es/grupo/>

simultaneously. Moreover, quantum machine learning algorithms can provide various advantages by using quantum computing's principle, including the: i) improvement of the run time, ii) advanced learning efficiency, and iii) advanced learning ability (increase in the capacity of content-addressable memory) [2]. Considering the advantages of quantum machine learning algorithms and their potential to be applied to NLP, novel research lines are being explored, such as Quantum NLP (QNLP).

QNLP is a novel interdisciplinary field that combines quantum computing principles with NLP techniques [3, 4]. It aims to harness the unique capabilities of quantum systems to tackle complex NLP problems, potentially offering significant improvements over classical approaches [5]. The motivation for merging quantum computing and NLP lies in quantum systems' ability to handle complex, high-dimensional data more efficiently [6]. Quantum computers could provide exponential speedups in tasks like semantic analysis [7], summarisation [8], text classification [9] and word embeddings generation [10], which are computationally expensive on classical systems. The parallelism and processing power of quantum computing make it an intriguing candidate for transforming NLP. Quantum algorithms could facilitate more advanced language models and techniques to grasp subtle nuances in textual data, as well as enable more efficient processing of long texts, improving the ability to condense information quickly. Quantum technology can perform faster computations and learn complex patterns from fewer data [11]. In short, quantum computing could revolutionise NLP by handling complex calculations far more efficiently than classical systems. It promises to accelerate machine learning algorithms, optimise NLP tasks, and drastically reduce training times for large language models through parallel computation and superior matrix handling.

Therefore, QUMLAUDE's primary objective is to investigate how quantum information representation and quantum algorithms can contribute to complex Natural Language Processing (NLP) tasks related to language understanding and generation (e.g., text simplification and summarisation). This includes exploring quantum-inspired algorithms capable of modelling linguistic phenomena, with a particular focus on semantic representation (e.g., contextual embeddings, semantic composition, metaphors) and other areas where quantum advancements could provide significant improvements. The aim is to achieve more precise and accurate results compared to current approaches, while making them more interpretable, transparent, and therefore, reliable.

The scientific novelty of QUMLAUDE lies in moving beyond the general application of quantum concepts to NLP by targeting specific unresolved linguistic challenges and connecting them with current AI architectures. While LLMs have achieved remarkable progress, they remain strongly dependent on statistical regularities and still struggle with phenomena such as anaphora resolution, word sense disambiguation, and metaphor interpretation. QUMLAUDE will investigate how quantum theory can model grammatical and compositional relationships in multidimensional vector spaces, and will explore pure-quantum, quantum-inspired, and hybrid classical-quantum approaches integrated with LLMs and RAG systems. In addition, the project introduces a generation-oriented perspective by framing summarisation and simplification as information selection and generation problems that can be represented through quantum circuits and optimised using quantum principles.

2. Project Objectives

The primary objective of the project is to investigate how quantum information representation and quantum algorithms can contribute to complex NLP tasks related to language understanding and generation (e.g., text simplification and summarisation). This includes exploring quantum-inspired algorithms capable of modelling linguistic phenomena, with a particular focus on semantic representation (e.g., contextual embeddings, semantic composition, metaphors) and other areas where quantum advancements could provide significant improvements. The aim is to achieve more precise and accurate results compared to current approaches, while making them more interpretable, transparent, and therefore, reliable. In particular, QUMLAUDE project is guided by the following key objectives:

- OB1. To analyse and establish how to apply quantum theories to the representation of texts identifying current limitations and challenges.

- OB2. To study the state of the art on available quantum algorithms and frameworks for NLP.
- OB3. To explore different optimisation mechanisms that can be used to propose either pure quantum models or hybrid models combined with LLMs and compare them.
- OB4. To research, propose and develop novel NLP approaches that integrate the principles of quantum information theory for language understanding and generation tasks (e.g., text simplification and summarisation) and the linguistic phenomena involved in them related to the semantic representation of text, such as contextual embeddings, knowledge graphs, word sense disambiguation, anaphora resolution, or metaphor interpretation.
- OB5. To design and develop a specialised RAG (Retrieval-Augmented Generation) system for retrieving and generating information on innovation. This system will integrate advancements in QNLP tasks developed within the project, such as contextual embeddings, semantic composition, knowledge graphs, anaphora resolution, metaphors, and other areas where quantum advancements can provide significant improvements. This use case will serve as an experimental platform and testing ground to evaluate intrinsically and extrinsically the impact and effectiveness of the developments in NLP, ensuring a practical and results-oriented approach.
- OB6. To promote and disseminate the research results obtained from the project through different national and international media—including well-indexed journals, conferences, seminars, etc.—as well as exploit the potential for transferring this technology to society.

3. Duration and Work Plan

QUMLAUDE started on 1 September 2025 and will run until 31 August 2028, with a total duration of three years. The research work to be addressed in QUMLAUDE has been organised into six modules (M) whose tasks and results are interlinked. Figure 3 shows a graphical description of QUMLAUDE’s work plan, including the modules and the tasks comprising each of the modules. Besides the transversal modules of coordination and dissemination of the project, the core scientific modules are briefly described as follows:

- **M1: Quantum representation of the text.** The aim of this module, related to OB1, is to analyse how natural language could be modelled under the quantum theory, identifying the challenges and opportunities to employ this theory in text representation. According to Coecke et al. [12], language is “quantum native”, as for instance, the superposition state of quantum mechanics can be used to represent multiple meanings of a word. This perspective is mainly based on two reasons: i) Quantum theory and NLP use vector spaces for describing states, which implies that natural language naturally fits on quantum hardware [13]. ii) The composition of words in a sentence corresponds to the composition of circuits representing words. This results in a circuit that prepares a state encoding the meaning of a sentence and could be directly transformed into a quantum circuit [9]. In 2016, Zeng and Coecke [14] proposed the creation of a new paradigm for NLP in a quantum computing context. Further, formal mathematical representations, such as QWIRE [15] or Distributional Compositional Categorical (DisCoCat) model of language meaning [16, 12] were proposed.

Therefore, in this module, these and other potential ways of formalising language via quantum theory will be deeply explored, analysing their capabilities and limitations for language understanding and generation tasks. Attempts to represent language using these formalisms for Natural Language Understanding (NLU) and Natural Language Generation (NLG) tasks have been already tested [3, 17], and could constitute a starting point for our project, as these tasks are currently formulated to a very limited extent (the generation of very simple short sentences in NLG, as for instance, DisCoCat, is not capable of modelling the meaning of large pieces of text). Two tasks involved in this module, which are:

Task 1.1. Analysis of quantum theory and how to apply it to text representation. As aforementioned, previous work has shown that the nature of text fits within quantum theory, so

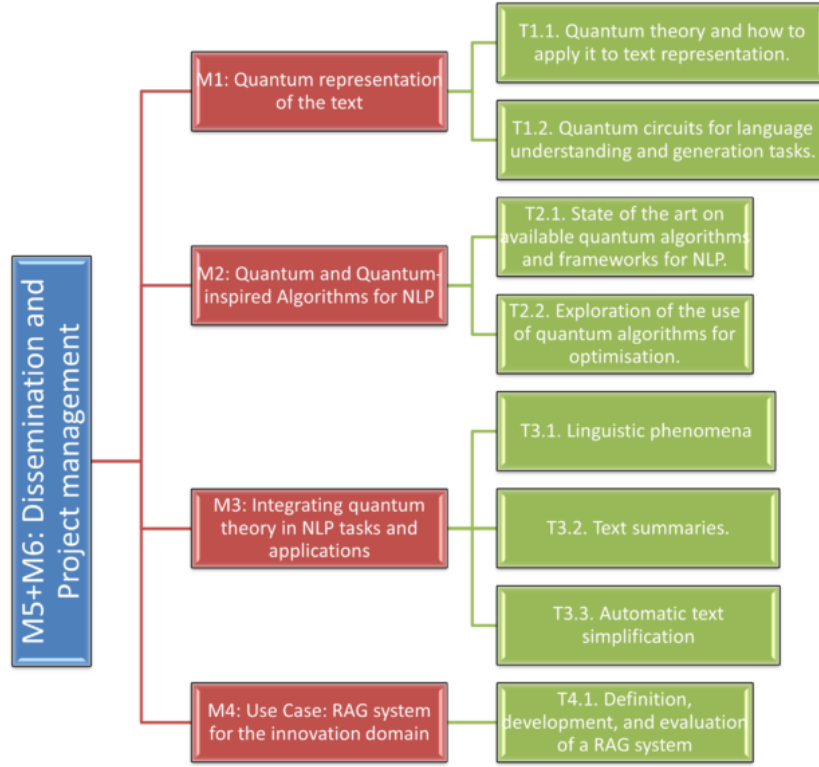


Figure 1: Summary of QUMLAUDE Modules and Tasks.

we will compile the state of the art about the existing methods to represent text together with their potentials and limitations.

Task 1.2. Defining quantum circuits for language understanding and generation tasks.

In this task, we will deeply explore how to build quantum circuits from text using DisCoCat or other mathematical formalisms that could model the semantics of a text (Galofaro, Toffano, and Doan, 2018). With the acquired knowledge, we will define the roadmap to follow to be further applied to NLP tasks and applications.

- **M2: Quantum and Quantum-inspired Algorithms for NLP.** The goal of this module, related to the specific objectives OB2 and OB3, is twofold. On the one hand, we aim to determine how quantum theory could be integrated into classical algorithms, for instance, for optimisation purposes, resulting in hybrid classical-quantum algorithms. On the other hand, we would like to explore novel quantum or quantum-inspired algorithms or improve existing ones. In both cases, the developed algorithms would be later applied to solve NLP tasks and applications related to text understanding or text production. In particular, these include summarisation, simplification, and RAG systems for retrieving and generating information, which corresponds to use cases defined in modules 3 and 4. In this context, algorithms at the intersection of NLP and quantum physics can be implemented either on quantum computers or classical computers. The former ones are usually called quantum algorithms, and the latter ones are usually named quantum-inspired models [18]. Both types of algorithms can model different features in the language. In this context, we find several lines of research related to Quantum Machine Learning [2, 13], Quantum Deep Learning [19] or Quantum-Inspired Machine Learning [20], this latter focusing on developing classical machine learning algorithms inspired by principles of quantum mechanics within a classical computational framework. These include algorithms, such as Quantum Support Vector Machine [21], Quantum Convolutional Neural Network [22], Quantum Recurrent Neural Network [23], Quantum Generative Adversarial Networks [24] or Quantum-Inspired language models [25], among others, that have been shown superior accuracy over their classical counterparts.

Another interesting application of quantum algorithms is directly related to optimisation to achieve faster and more effective results [26]. This could include novel approaches in which quantum-based solvers may be used in tasks related to feature selection [27], relevant for NLP applications, such as information retrieval, text classification, summarisation, or simplification. The QuantumCLEF shared tasks, proposed for the CLEF 2024 [28] and CLEF 2025 [29] conferences, provide a promising starting point to analyse existing approaches in this area and address the issue. The two tasks comprising this module are: **Task 2.1. Analysis of the state of the art on available quantum algorithms and frameworks for NLP.** A comprehensive review of the literature on quantum algorithms will be performed. The different approaches will show how quantum theory has been applied and allow us to select those more feasible to be based on in our project and make improvements over them, towards the goal of evaluating and comparing pure quantum, quantum-inspired or hybrid models, together with their level of interpretability and transparency.

Task 2.2. Exploration of the use of quantum algorithms for optimisation. In this task, we will study, test and evaluate various means of quantum optimisation approaches that might aid the long-term efficiency of NLP tasks and applications. To this end, common implementations of well-known algorithms will be collected and compared. Similar NLP problems already applied to quantum computing will also be analysed and effective approaches will be adapted to the tasks, applications and scenarios proposed in the M3 and M4 modules. Relevant benchmark problems will be defined at various classes of size and difficulty. All approaches will be compared to classical state-of-the-art and classical problem-specific adaptations.

- **M3. Integrating quantum theory in NLP tasks and applications.** Once we have determined both the best way to represent the information contained in a text using quantum theory (M1) and the way to integrate quantum algorithms for NLP (M2), this module, related to OB4, will analyse the possible scenarios for the application of these findings. To do that, it is essential to first analyse how to model several linguistic phenomena, with special attention to areas where quantum advancements could provide significant improvements, achieving more accurate and precise results compared to current approaches. Three main tasks will be addressed, one of them related to text understanding of linguistic phenomena and the other two to text production, specifically text summarisation and text simplification. Three tasks are proposed for this module: **Task 3.1. Exploration of quantum NLP approaches to resolve linguistic phenomena.** In order to analyse how quantum theory can help to improve NLP tasks related to text understanding and generation, it is necessary to analyse those aspects related to these tasks where current approaches are not able to provide robust results. Therefore, phenomena such as anaphora resolution, word sense disambiguation or metaphor resolution will be investigated.

Task 3.2. Exploration of quantum NLP approaches to perform text summaries. This task aims to formalise the summarisation problem using principles from quantum theory, offering a novel perspective on how summarisation can be viewed and optimised as an information selection and generation problem. From the knowledge acquired in modules 1 and 2, and task 3.1, quantum circuits will be used to represent and model the summarisation process, potentially leading to breakthroughs in efficiency and accuracy. Then, quantum-inspired optimisation processes would be used to conduct summarisation modelling for fitness evaluation, taking as a basis the ideas already investigated using classical optimisation algorithms [30, 31].

Task 3.3. Exploration of quantum NLP approaches to perform automatic text simplification. Following the same guidelines as for the previous task (task 3.2), this task aims to analyse how to optimise the automatic text simplification process using the principle of quantum theory. Although several studies have been carried out so far on the automatic simplification of texts, not all the aspects to be simplified have been solved to the same extent. While linguistic obstacles such as numbers, superlatives, acronyms, enumerations or simple appositions have sufficiently robust solutions (see as an example SIMPLE.TEXT tool [32] at <https://simpletext.demos.gplsi.es/>), other types of obstacles such as some cases of difficult words or complex sentences still require some effort on the part of the scientific community so that the results obtained can really be of

use to society (Saggion, 2024; Martínez, et al., 2024). Therefore, in this task, novel perspectives based on quantum algorithms will be studied to obtain substantial improvements in the automatic text simplification processes.

- **M4. Use Case: Retrieval Augmented Generation system for the innovation domain.** This module, related to OB5, aims to design and develop a specialised Retrieval-Augmented Generation system (RAG) for retrieving and generating information on innovation. This system will integrate advancements in QNLP tasks developed in M1, M2, and M3. This use case will serve as an experimental platform and testing ground to intrinsically and extrinsically evaluate the impact and effectiveness of the developments in NLP, ensuring a practical and results-oriented approach. A RAG search system is a technique in AI that combines information retrieval with text generation [25].

The process involved in a RAG comprises the following 3 stages: 1) Information Retrieval: the system retrieves relevant information. 2) Enrichment: the retrieved results are used as additional context to guide the language model. This allows the model to produce answers that are not only linguistically consistent but also supported by relevant data or information. 3) Response Generation: once the system has access to the retrieved documents, a language model (such as GPT or similar) uses this information to produce a response tailored to the query. The result is a more accurate and contextualised output compared to generative models that do not incorporate search.

Task 4.1. Definition, development, and evaluation of a RAG system for the innovation domain. The objective of this task is to define, develop and evaluate a RAG system for the innovation domain that uses and integrates the results obtained in M1, M2 and M3. In addition, in the last RAG stage concerning language generation, the impact on LLM in the generation of summaries and simplified text will be evaluated and a comparison of classical and quantum-based approaches will be conducted.

4. Evaluation Protocols, Datasets, and Benchmarking

Experimental Platform and Protocols. The evaluation framework utilises a specialised Retrieval-Augmented Generation (RAG) system (Module 4) within the innovation domain as its primary experimental platform. Guided by an Agile methodology to facilitate continuous empirical assessment, the project conducts both intrinsic and extrinsic evaluations of the proposed architectures. Specifically, Task 4.1 investigates the impact of quantum logic on Large Language Models (LLMs) during generative tasks, such as text summarisation and simplification. Model viability is rigorously quantified across two primary metrics: *efficiency* (temporal, spatial, and advanced learning resource allocation) and *accuracy* in applied generation tasks.

Data Strategy and Corpora. To ensure findings can be reliably extrapolated to practical applications, evaluations prioritise sampled real data, deliberately shifting away from the artificial datasets prevalent in current QNLP mathematical demonstrations. To mitigate the challenge of quantum data scarcity, we will leverage our established expertise to engineer specialised corpora tailored for complex QNLP tasks. All data management will strictly adhere to FAIR (Findable, Accessible, Interoperable, and Reusable) principles. Resulting datasets will be fully anonymised for GDPR compliance and catalogued in open-access repositories.

Benchmarking and Comparative Analysis. We adopt a comprehensive benchmarking strategy to directly compare pure-quantum, quantum-inspired, and hybrid models against classical state-of-the-art (SOTA) baselines (Task 2.2). This framework incorporates community-standardised evaluations, utilising QuantumCLEF shared tasks (2025/2026) to analyse feature selection and optimisation. Furthermore, problem-specific benchmarks will be defined across varying classes of scale and computational difficulty.

The evaluation culminates in a head-to-head performance comparison of classical versus quantum-enhanced models operating live within the RAG environment, providing concrete proof of performance differentials.

5. Expected Scientific Impact

By bridging quantum information theory and NLP, this project will contribute to theoretical foundations and practical applications, reinforcing Spain and Europe's position as a global leader in AI and quantum research. It will also act as a catalyst for interdisciplinary collaboration among computational linguists, physicists, and AI specialists. We aim to transform NLP tasks and attract the interest of the NLP and AI research communities worldwide. When it comes to the expected scientific-technical or international impact, our proposal presents expected advancements in four key areas:

- Advancements in mathematical and computational modelling of text processing (interpretation and generation): We expect to surpass current neural models, based solely on statistical information, and complement them with quantum models that allow for modelling grammatical and compositional relationships in multidimensional vector spaces.
- Addressing complex linguistic phenomena: Addressing linguistic phenomena, such as anaphora, semantic ambiguity, or metaphors from a quantum paradigm will enable new models that take into account previously unconsidered aspects.
- Optimisation of algorithms for quantum computing, by adapting algorithms from NLP to quantum computing.
- Integration of advanced AI techniques into quantum models. Techniques such as RAG and LLMs are to be improved for tasks such as text simplification and automatic summarisation.

Declaration on Generative AI

The author(s) have employed Generative AI tools (i.e. ChatGPT) for proofreading and checking spelling issues.

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