

EXPLORING THE CEREBRAL ACTIVITY THROUGH MUSIC AND VISUALS.

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SUMMARY

SUMARIO

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0.1 HÈCTOR

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ACRONYMS

INTRODUCTION

1.1 MOTIVATION AND RESEARCH PROBLEM

This project was motivated by a mix of academic interests and personal experiences. A strong curiosity for both audio and video has always been shared by us. Coming from backgrounds in audiovisual engineering and graphic design, we tend to approach creations with a critical and analytical eye. When it came time to choose a topic for our final master's project, we realized quickly that our interests were closely aligned. After engaging in numerous in-depth dialogues, we arrived at the decision to concentrate our research into two primary areas: the realm of visuals and music, along with the dynamic interplay between these two forms of expression. This intersection felt like the natural place where our skills, passions, and professional perspectives converged.

As we continued our research, we observed that in live shows, the visuals often had little or no meaningful connection to the music. Many visual productions are undeniably impressive. The work of Anyma is an example of this. However, these productions tend to function primarily as aesthetic elements. Rather than enhancing the auditory experience or accentuating the distinctive attributes of each composition, the visual elements often prove to be a source of distraction.

We also discovered that a significant number of artists rely heavily on tutorials for creating their visuals. Tools like TouchDesigner, widely used in the industry, offer powerful capabilities for generating dynamic visual content. The platform offers numerous step-by-step tutorials aimed at beginners, guiding them through the creation of basic visual effects. However, we were surprised to find that even at major, internationally recognized festivals, some artists were using visuals that were essentially the same basic tutorial outputs, sometimes with only minimal modifications. This highlighted a gap between the potential of the technology and the creative depth actually being applied in many professional contexts.

1.2 HYPOTESIS AND OBJECTIVES

The issues surrounding the current use of visuals were recognized, and it was decided that this challenge would be made the foundation of our thesis. Since TouchDesigner has been a key tool throughout the Master's program and is widely regarded as a primary platform for creating visuals, we formulated the following research question: **Is it possible to develop a system within TouchDesigner that helps artists create visuals more easily?**

The rapid growth of artificial intelligence and the increasing accessibility of LLM-based tools, such as Microsoft Copilot and Cursor, are giving rise to new workflows that integrate AI directly into creative and professional environments. These advancements indicate that AI has the potential to play a significant role in supporting or even improving digital creation processes. Our concept is to incorporate artificial intelligence into TouchDesigner, empowering users to customize its training according to their unique requirements and artistic inclinations. This would enable artists to generate unique visuals more efficiently and reduce their dependence on generic tutorials, encouraging more personalized and innovative visual production. Based on that hypothesis, the next objectives were proposed to accomplish the project:

- **O₁ Research and training:** The first objective is to establish a solid research foundation for training LLM-based agents. The tool is intended to be customizable so that each artist can adapt it to their own creative workflow. This initial stage will involve selecting a specific artist as a reference case. The goal is to identify a viable method for training an LLM-based model and subsequently integrating it into TouchDesigner. This requires selecting an appropriate model, determining how to structure and transform information so that it can be effectively learned by the model, and implementing a workflow that enables seamless integration within the TouchDesigner environment. Achieving this will ensure that the system can operate reliably and support the intended creative processes.

- **O₂ Creation of the tool:** The second objective focuses on developing the tool within TouchDesigner. This stage involves building a network of AI-driven agents that are trained using the research compiled in the first objective. The goal is for this network to support a wide range of creative tasks, such as modifying colors and shapes, generating shaders, and producing audio-reactive visuals. Users should be able to accomplish these tasks by either providing an example visual or entering a prompt. In the end, this system tries to make the creative workflow more efficient and give artists the ability to create more personalized, expressive visuals more easily.

2

THEORETICAL FOUNDATIONS

2.1 VISUAL HISTORY

The world of screen visuals is a rapidly evolving field that brings together art, technology, and design. Far from being limited to the simple reproduction of images, this discipline encompasses a wide range of techniques, styles, and audiovisual tools. It includes everything from digital manipulation and real-time rendering to generative art and immersive installations. Today, visuals play a central role in technological art, contributing not only to aesthetic expression but also to musical and interactive experiences.

The origins of this practice can be traced back to the 1960s with the introduction of Sony's Portapak, the first portable analog video recorder, shown in figure 1. This device made it possible for creators to experiment with video outside of traditional television studios, opening the door to new forms of artistic expression. Among the first to explore its possibilities was Nam June Paik, who used magnets and electromagnetic filters to distort electronic images and create innovative visual effects[6, 14]. At the same time, artists such as Steina and Woody Vasulka focused on developing analog synthesizers capable of modulating waves and altering electronic signals in real time [18]. Although these early explorations often intersected with scientific experimentation, they laid the foundation for what would eventually become a recognized artistic field.



Figure 1: Sony Portapak camera (Maison de la Vidéo & du Cinéma: [9])

During the 1980s and 1990s, with the advent of digital video, new techniques for editing, production, and temporal manipulation emerged. At this point, artists such as Bill Viola began to explore new techniques using extreme video slow motion and careful compositions [19]. Pipilotti Rist experimented with modifying images by altering saturation and distorting them to create expansive projections [17]. At the same time, in the field of electronic music, VJing was invented, a practice that consisted of mixing images in real time while music was playing. This concept quickly grew with the development of software such as Modul8, VDMX, and Resolume [16].

Starting in the early 2000s, the availability of powerful computers, advanced graphics cards, and high-brightness projectors profoundly transformed visual creation processes. These tools, which were once static, have evolved into dynamic systems capable of generating images in real time, responding to external data, and integrating with sensors or interactive devices. Rather than approaching visual creation as a fixed, pre-defined product, it became possible to use environments such as TouchDesigner, Max/MSP/Jitter, and Pure Data to create a visual experience as a modulable data flow [3].

Concurrently, languages such as Processing and p5.js enabled the growth of generative art, empowering algorithms, mathematical frameworks, and computational logic to dictate the structure and behavior of images [12]. Consequently, the role of the

visual artist underwent an evolution, becoming a hybrid profile that integrates design competencies with programming acumen and technical experimentation. Visual creators shifted from operating tools to becoming system architects who can manage complex information flows to produce flexible, interactive audiovisual experiences.

Today, screens have expanded far beyond the traditional rectangular device, with new options including curved screens, foldable screens, and screens with various sizes and shapes. These elements can now manifest in various forms, including architectural surfaces, immersive environments, interactive installations, and high-resolution urban displays. Sensors, depth cameras, body-tracking devices, and real-time analysis systems are integrated to allow artworks to react to the presence and actions of the audience, creating multisensory experiences in which the image behaves like a living environment. As Paul [11] notes, contemporary digital art operates in a hybrid space where physical materiality and computational logic converge, thereby transforming the relationship between viewer and artwork.

This landscape is defined by its technical diversity and complexity. A variety of tools and methods from different fields are used to create screen-based visuals. These fields include composition, animation, programming, interaction design, data visualization, digital scenography, and algorithmic systems. Therefore, an interdisciplinary territory is worked in by the contemporary artist, and mastery of both aesthetic strategies and technological capabilities is required. The screen is no longer merely a display surface but an expanded field where human creativity, electronic processes, and computational structures intersect. The way it keeps changing reflects the big impact of new technology on modern art and the way it moves towards using visual practices that go beyond the usual limits of images and exhibition spaces.

2.2 TOUCH DESIGNER

TouchDesigner is a real-time visual development platform developed by Derivative that is used extensively for the creation of interactive multimedia systems, data-driven visualizations, and generative art. The architectural framework of this

system is predicated on a node-based procedural workflow, a methodology that empowers creators to construct intricate systems by establishing connections between functional units designated as operators [4]. This modular approach is conducive to iterative design and facilitates the utilization of TouchDesigner by both artists and technically oriented users, aligning with the broader tradition of visual programming tools in new media [7].

A significant advantage of TouchDesigner is its capacity for real-time rendering and data processing. This enables the manipulation of video, 3D geometry, audio, and sensor inputs with minimal delay. The software's capacity to perform such functions has led to its central role in the creation of large-scale audio-visual installations, projection mapping, interactivity in stage design, and immersive experiences [1]. Its real-time nature situates the platform within contemporary practices of live media and performance technologies, where responsiveness and dynamic interaction are essential [2].

The TouchDesigner workflow is organized into specific categories of operator, namely TOPs, CHOPs, SOPs, DATs, and COMPs. Each operator category has been designed to process a particular data or execute a specific process. This layered structure enables creators to transition between surface-level interaction design and more profound computational logic [8]. The platform utilizes Python as its scripting environment, providing advanced control, automation, and logic-based behavior for interactive systems [15]. TouchDesigner's integration of visual programming with textual scripting positions it at the nexus of creative coding environments, such as Processing [13], along with live coding paradigms that have been explored within performance contexts [10].

2.3 LOPS

LOPs (Language / Learning / Logic / Latent Operators) is a modular AI framework designed to deeply integrate artificial intelligence into TouchDesigner created by DotSimulate. Its tool ecosystem allows AI agents to reason, search, perceive, remember, and act directly inside node-based visual workflows. Every LOPs tool is implemented as a TouchDesigner operator and can expose its functionality to AI agents through a standardized tool interface, enabling structured, reliable AI-driven execution.

At the center of the system is the idea that AI is not a black box, but an active participant in the network, able to inspect context, call tools, retrieve information, manipulate data, and respond in real time.

- **TextCore AI Controllers**

The **Agent operator** is the main intelligence hub. It manages conversations, system prompts, context windows, streaming responses, and tool execution. The Agent dynamically decides when to call tools, passes structured arguments to them, and incorporates their results into its reasoning. It supports text, image, and audio context and acts as the orchestrator for all AI workflows.

Gemini live extends this functionality into real-time, multimodal interaction. It enables live voice conversations using speech-to-text and text-to-speech, supports continuous streaming input/output, and allows AI agents to call tools during spoken conversations. This makes it suitable for installations, performances, and interactive systems.

The **Role creator** tool assists in dynamically generating system prompts and AI personas. Instead of manually crafting long instructions, users can generate specialized AI roles such as tutor, analyst, creative assistant, which can then be assigned to agents.

- **Tool Management and Context Awareness**

The **Tool Registry** automatically discovers all available tool operators in a project and makes them accessible to agents. This removes the need for manual configuration in complex networks and allows scalable multi-agent setups.

The **Tool Monitor** provides agents with awareness of user activity inside TouchDesigner. It tracks selected nodes, parameter changes, errors, and interaction events, allowing the AI to respond intelligently to what the user is doing in real time.

The **Network Context** tool exposes structural information about the TouchDesigner network—operators, connections, and layout—so agents can reason about the project itself.

- **Search, Web, and Data Acquisition Tools**

The **Search operator** enables AI-driven queries across multiple search providers and data types. Agents can autonomously perform web searches, retrieve results, and integrate them into their responses.

Source Webscraper crawls websites while respecting rate limits and robots.txt, extracting clean text into tables.

Source Crawl4AI uses a headless browser to render modern websites and export content as structured Markdown, suitable for large-scale crawling.

textSource GitHub ingests repositories, issues, documentation, and code for knowledge extraction.

Source Docs parses local documents (HTML, Python, Markdown, etc.) into indexed tables.

Source Ops extracts information directly from TouchDesigner networks, turning operators and parameters into searchable knowledge.

The **Save Sources** operator persists scraped or generated content as Markdown files, allowing datasets to be reused or indexed later.

- **RAG and Memory Workflows**

LOPs supports Retrieval-Augmented Generation by allowing content to be indexed and retrieved dynamically. While the indexing and retrieval operators work behind the scenes, the overall workflow enables agents to pull relevant information from large datasets instead of relying solely on their prompt context. This allows scalable knowledge bases, documentation assistants, and project-aware AI systems.

- **Integration and External Tooling**

The **MCP Client** connects TouchDesigner to external tools using the Model Context Protocol (MCP). This allows agents inside TouchDesigner to call tools hosted outside the application, extending LOPs beyond local functionality and enabling distributed AI systems.

- **Utility and Data Manipulation Tools**

Several tools focus on enabling AI-controlled manipulation of TouchDesigner data:

Tool DAT allows agents to read, write, and modify table data programmatically.

Tool Parameter lets agents change operator parameters in a structured, validated way.

The Super Select operator enhances table manipulation with advanced filtering and fuzzy selection, making it useful for preparing data before AI processing

- **Environment and Dependency Management**

The Python Manager automatically manages Python virtual environments and dependencies required by LOPs operators. This ensures stability and reduces setup friction, allowing complex AI pipelines to run reliably inside TouchDesigner

All of this information, along with usage examples, installation tutorials, recommendations, and additional technical details, is available in the official LOPs documentation [5].

2.4 LARGE LANGUAGE MODELS (LLM)

A large language model (LLM) is an artificial intelligence system designed to communicate with humans. These systems can understand, generate, and reason with human language. Essentially, it reads inserted text and predicts what text will come next based on it. By repeating this process, the system produces coherent language. These systems essentially seek to mimic human reasoning by learning statistical patterns from large amounts of text.

These models perform a task called next token prediction. For instance, when the phrase "The capital of France is" is entered into the system, the model predicts "Paris." This interaction creates a token, which can be a word, part of a word, a punctuation mark, and so on. After performing these processes repeatedly, the system acquires more complex behaviors, such as writing essays, answering questions, translating, and

writing code. Before the text can be processed by the model, it must first be converted into tokens. Each syllable or word is converted into a token and assigned a numerical identifier. Approximately 30,000-100,000 tokens are needed to translate a text. This mapping of tokens can be imagined as large matrices containing lists of numbers. The more similar the words are, the more similar their vectors will be. This process is called "embedding." With each interaction, the model uses a process called "self-attention," which involves looking at all previous tokens to decide which ones matter most for predicting the next one. In this way, weights are assigned to previous tokens based on their relevance. Rather than using just one attention mechanism, these models use many in parallel, each responsible for a specific topic. This approach achieves better understanding and greater linguistic richness. After applying these weights to each token, each token goes through a neural network to introduce nonlinearity and abstraction. This enables the model to learn more complex concepts.

These models are designed to be trained using large amounts of data, such as books, articles, web pages, and repositories. Artists using the tool developed in this project can use it to train the model with all their research, color patterns, shapes, and any relevant files. LLMs learn by masking text and predicting missing or future tokens while minimizing prediction errors. After pre-training, models are refined using examples of specific commands, human feedback, or counterfactual datasets. Once the model has been trained and refined, it can generate text based on a user-generated prompt. As the user types, the prompt is converted into tokens that pass through the model. The probabilities of the next token are then calculated and the token selected using a sampling strategy.

One of the characteristics of these models is that they do not think like humans or act logically. They learn patterns and imitate logical steps based on their training, making them very powerful tools for solving multi-step problems or generating analogies. However, they will fail if asked to do something outside their training parameters. This can result in the generation of false but plausible information, as well as a false sense of security due to invented sources. As they have no consciousness or grounded experience, they can only remember what they have previously seen and are incapable of retaining memory. In other

words, they cannot retain past information in order to hold a conversation with the user on their own.

3

RESEARCH

3.1 INTRODUCTION

For the practical part of the project, the focus will be on accomplishing all the objectives. The proposed approach is to first investigate and define an effective method for training the model, and only then proceed with the development of the tool itself. Since the project is intended for use by artists, a reference artist with a well-defined visual identity, particularly in terms of color palette and formal language, was selected. This choice makes it possible to clearly demonstrate how the system generates visuals that are informed by and aligned with the artistic characteristics of the chosen individual. This will allow each artist to adapt and modify it according to their own creative needs. The development process will center on a single case study. To simulate an artistic profile, the decision was made to use the color palettes of Antoni Gaudí.

Gaudí was a renowned Catalan architect whose work is characterized by organic, curved forms that evoke elements of religion and nature. His architectural language combined structural innovation with strong symbolic and aesthetic intent.

One of the most distinctive techniques associated with Gaudí is trencadís, a modernist method that involves covering surfaces with fragments of broken ceramic tiles. As seen in figure 2, this technique allowed for the creation of vibrant, textured surfaces and complex color compositions, which have become a defining feature of his work. The use of Gaudí's color palettes and formal principles provides a clear and recognizable visual reference, making it well suited for simulating an artist-driven visual system within the project.



Figure 2: Images of Gaudí’s Architecture

This material will serve as the foundation for training our system. By grounding the tool in the specific characteristics of his music, we aim to create a version of the project that reflects his artistic identity and demonstrates how the system can be tailored to other artists.

3.2 TRAINING OF THE LLM

In order to properly train the system, information on several different topics will be collected to carry out the entire research process. Several approaches were explored in order to train the LLM models. While the objective was clearly defined, to integrate a trained model into TouchDesigner and enable interaction directly within the application, the specific method for achieving this integration was not initially known. As a result, different strategies were investigated and evaluated to determine the most effective way to train the model and connect it to the TouchDesigner environment.

3.2.1 First approach

The first approach involved manually creating all the information required for the LLM models. As explained in the REFERENCE section, for a model to acquire and use information, it must pass through several distinct stages. First, a document containing the relevant and curated information must be created. Next, this data must be embedded so that the model can process and analyze it effectively. Finally, the model must be connected to the processed data, enabling it to retrieve and use the appropriate information in response to user queries.

The first thing was to recollect all the information that the model has to learn. To start researching, as one of the aspects that the project wants to cover was the colour, a research of academic papers based on colour started. After several hours of analysis, approximately 60–70 papers were selected for each topic, prioritizing those that offered the most reliable and impactful insights for the tool’s development.

Once the papers had been selected, the next step was to construct the database. To organize the information systematically, a CSV file was created to store and classify the key details from each article. The following structure, shown in Figure 3 was chosen:

- **Title**
- **Author**
- **Year**
- **Summary:** This section contains a condensed version of the paper’s abstract. Because abstracts are typically accessible for free, they provide enough information for the system to understand the essence of each study without requiring full-text access.
- **Keywords:** Keywords were included to enable the system to retrieve the most relevant papers based on the prompts provided by the user. When embeddings are generated, these keywords help the system match user queries with the scientific articles that best fit the topic, ensuring accurate and efficient information retrieval.

This structured approach ensures that the agent can navigate the database effectively and rely on well-organized, high-quality scientific data.

1	hours, year, summary, keywords
2	"Georgopoulou, K. R. & Kiper, D. C.", 2003, "This paper reviews the neural mechanisms underlying color perception in humans. It describes how the retina encodes color demonstration of functional specialization in human visual cortex", "Zeki, S.", 1991, "This study demonstrates that the human visual cortex is organized into functionally critical stages of colour processing in the human brain", "Zeki, S.", 1998, "This paper describes three cortical stages in color processing in the human brain. The first occurs at the colour centre in the human visual cortex", "Bartels, A. & Zeki, S.", 2000, "This study analyzes the functional organization of area V4, considered the "color-cal encoding of color in the brain", "Bird, C. M. et al.", 2014, "This study investigates how the brain encodes colors into perceptual categories, using fMRI, the authors focus on color in the human visual cortex: an fMRI review", "Mullen, K. 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Figure 3: Example of a CSV with the Structure of the project

The next step involved processing the information contained in the CSV file. To ensure that the agent could generate embeddings effectively, it was necessary to remove any characters that might interfere with processing, such as accents, apostrophes, and other special symbols. These characters can cause inconsistencies or errors during embedding generation, so cleaning the data was essential.

To accomplish this, a script was created to automatically convert and sanitize the CSV files, ensuring that all entries were standardized and compatible with the agent's requirements. This script, titled `Papers_clean.py`, performs the necessary preprocessing steps and prepares the dataset for seamless integration. The full code for this script is included in the appendix B.1.

The next step was to create the embeddings. To do this, as we had some knowledge of Python but not of how to create embeddings, we used Cursor. Cursor is paid software similar to Microsoft Copilot, which allows you to program in an environment that has implemented artificial intelligence that allows you to read and analyze everything you are doing, as well as suggest possible improvements.

Basically, this code builds and tests a semantic search system for academic papers. It loads a cleaned CSV file containing

paper data and ensures required text fields exist. Each paper's title, summary, and keywords are merged into a single text string. A pretrained SentenceTransformer model converts these texts into numerical embeddings. The embeddings, original texts, and metadata are stored in a persistent ChromaDB vector database. Each document is assigned a unique ID and saved to disk for reuse. A test query in natural language is also converted into an embedding. The database is searched for the most semantically similar papers to that query. The top matching documents are retrieved based on meaning, not keywords. Finally, the script prints the titles, metadata, and text snippets of the best results. For watching the full code, go to the annex [B.2](#)

The subsequent step was to integrate the generated embeddings into TouchDesigner. However, during one of the meetings with Sabio, the possibility of working with LOPs was discussed. LOPs is a TouchDesigner-based system developed by DotSimulate that enables the integration of LLM-powered agents directly within the software. After conducting further research, it became evident that LOPs significantly simplified the workflow. Unlike the initial approach, it was no longer necessary to manually perform all preliminary processing steps. Instead, by providing a folder containing HTML, HTM, or TXT files, it was possible to interact with an agent that had direct access to the knowledge supplied by the user. This discovery marked a turning point in the project, as it allowed the focus to shift from low-level implementation details to the design and behavior of the AI-driven system within TouchDesigner.

3.2.2 LOPS

When we started working with LOPS, it quickly became clear that it wouldn't be plain sailing. Due to incompatible versions of other software, such as Python, it took two weeks of errors just to install the tool within Touch Designer. Nevertheless, thanks to DotSimulate's helpful tutorials and his willingness to answer our questions, we managed to start working with the software. Once LOPS had been correctly installed, the research began and a much simpler way of training the model was discovered than that described in the [3.2.1](#) subsection. Training the LLM model involves fewer steps, and LOPS automates the process much more efficiently. However, before starting, two Gem-

ini 2.0 API keys had to be acquired, one for each team member. Ollama, an LLM model designed for local use, also had to be installed. This model enables the creation of embeddings. Below, we will explain how to train an LLM model and connect it to an agent, enabling you to access information based on a prompt.

- **Source Docs:** The first step is to incorporate all user-provided information into TouchDesigner. This is achieved using an operator called Source Docs. This operator enables users to reference a folder on their local computer and automatically read all documents stored in supported formats, such as .htm, .html and .py. These files collectively form the knowledge base that the agent will later use.

When the operator is opened in TouchDesigner, the configuration interface becomes visible, as seen in Figure 4. From here, users can define the folder path and manage how documents are ingested into the system. This ensures that all relevant information is correctly loaded and made available for further processing.

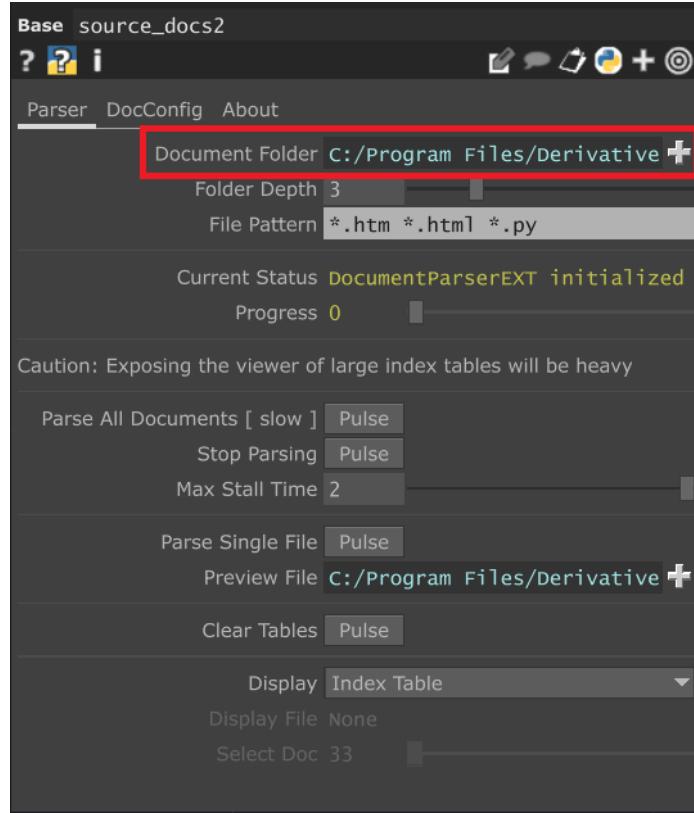


Figure 4: Place to select the Folder with all the documents to be embedded by the LLM

Once the folder has been selected, the documents must be parsed so that the system can correctly process their contents. The operator interface provides three main options for this, as shown in Figure 5.

The first option, 'Parse All Documents' (slow), processes all the documents in the selected folder in one operation. This method is useful when working with a complete dataset, although it may take longer depending on the number and size of the files. The second option, 'Parse Single File', processes each document individually, offering greater control when testing or updating specific files. Finally, the 'Clear Table' function removes all previously parsed data. This option is necessary when a document in the folder has been modified, as the existing data must be cleared and re-parsed to accurately reflect the changes.

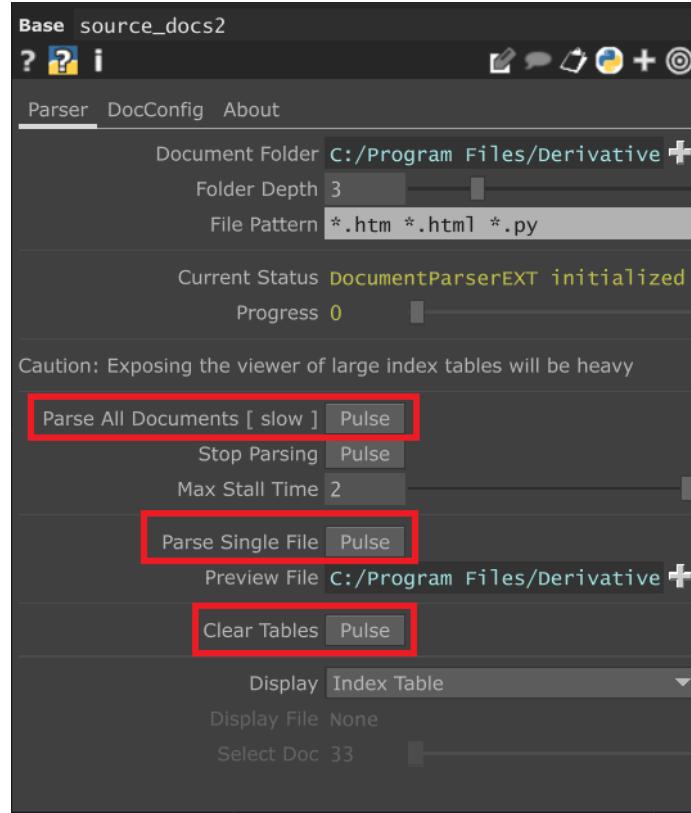


Figure 5: Options Parse All Documents, Parse Single File and Clear Tables

- **RAG index:** When all the documents in the folder that the user wants have been parsed, the next step, as shown in Figure , is to connect the 'RAG index'.

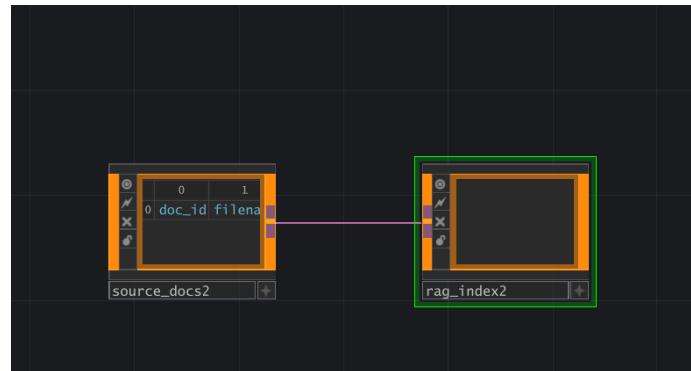


Figure 6: Connection between Source Docs and RAG index

This operator is responsible for processing all the documents provided by the Source Docs operator and generating the corresponding embeddings. As with the previous

operator, the RAG Index includes a drop-down menu that provides access to its configuration options. One of its key functions is allowing the user to select the LLM model that will be used for embedding generation and retrieval.

In this project, a local instance of the Llama 3 model was used, running through Ollama. Once the model is selected, the operator processes the ingested documents, creates embeddings from the parsed content, and builds the corresponding indexes that enable efficient information retrieval. These functionalities and configuration options are illustrated in Figure 7. Depending on each person's computer, this step is prone to errors. If you encounter an error at this stage, please refer to the appendix A.3.

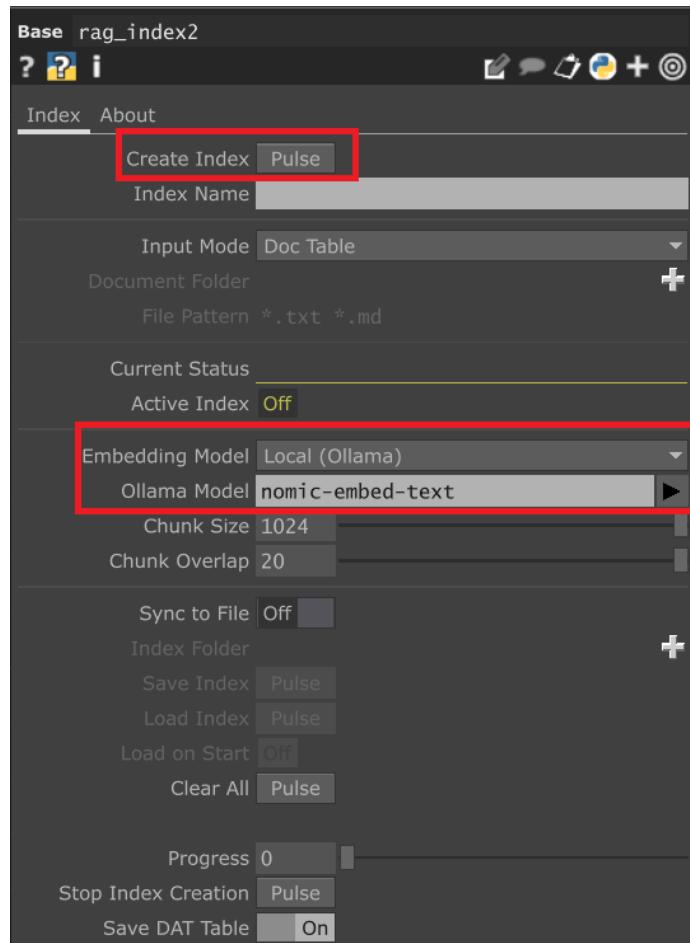


Figure 7: Options of the Rag index

Once the index is created, the index name will appear automatically. To verify everything is correct, an image like the Figure 8 should appear.

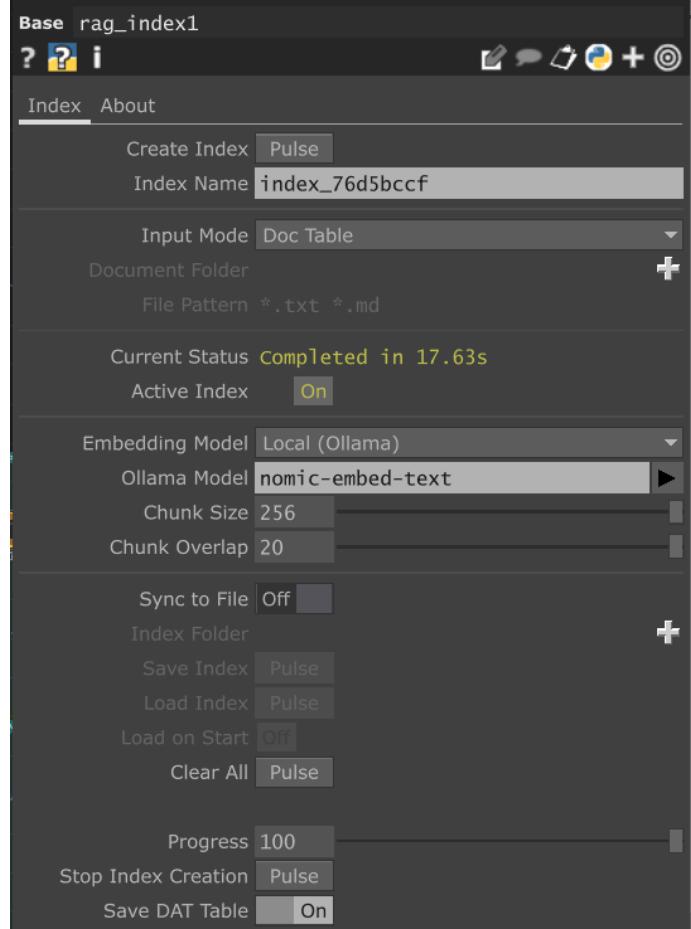


Figure 8: Index created

- **RAG Retriever:** Once the RAG Index has been created, the next step is to add a RAG Retriever operator. This operator must be linked to the previously generated RAG index in order to retrieve relevant information during user interactions.

As shown in Figure 9, this configuration is performed through the operator's parameters. In the Search Mode section, the Custom option must be selected. After enabling this mode, the desired RAG index should be dragged into the Query Phase section. Once the RAG components are correctly connected, the final step is to click the "Query Index" button. When this action is performed, the operator searches

the indexed data and retrieves the most relevant document fragments based on the information requested by the agent or the message entered in the Add Text section. These retrieved fragments are then used to provide context-aware responses, enabling the agent to answer queries accurately using the embedded knowledge base, as shown in Figure 10.

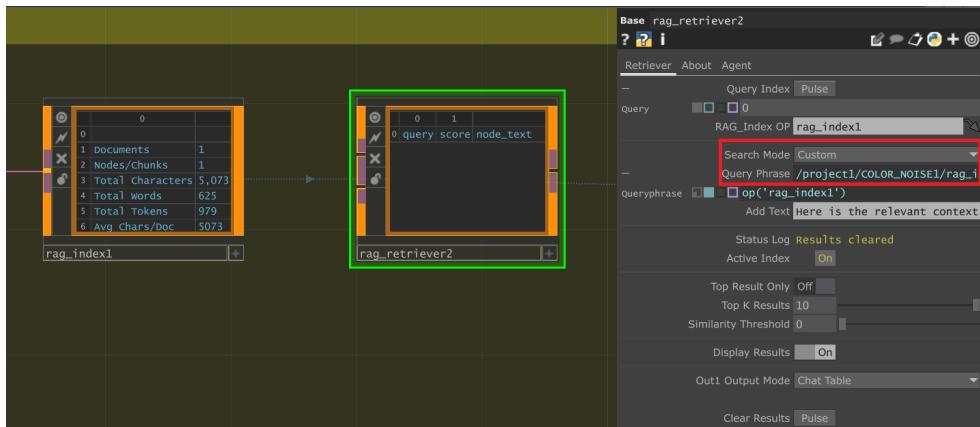


Figure 9: Connecting the rag index into the rag retriever.

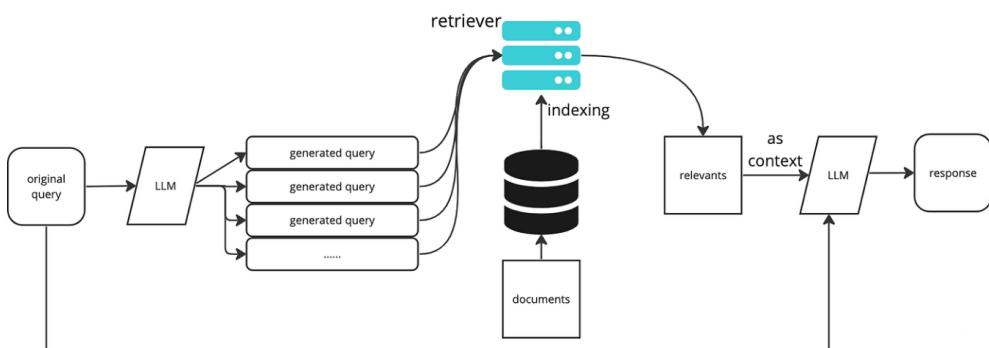


Figure 10: Diagram of how a Multi-Query Retrieval works

- **Agent:** Finally, an agent must be added and connected to the RAG Retriever. This enables users to interact with the system directly via the agent, which responds by retrieving and using the most relevant information based on user requests and knowledge stored in indexed documents.

To establish this connection, the agent's parameters must be configured accordingly. As shown in Figure 11, navigate to the 'Tools' tab and locate the 'External Tools OP' section. En-

able an external operator and drag the corresponding RAG Retriever into the designated field.

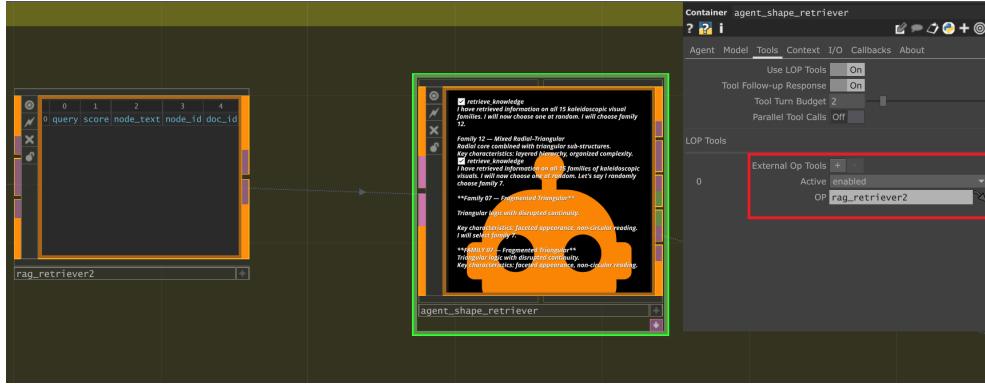


Figure 11: Adding the rag retriever into the agent.

Finally, once all operators have been properly connected, the agent must be configured to define its role and expected behavior. This is done by accessing the agent's parameters and specifying its system instructions.

To do so, navigate to the Agent tab and click the EditSysMess button. Within this field, the user can describe the agent's function, define its scope, and specify how it should respond to queries.

4

PROJECT PLANNING AND ECONOMIC STUDY

4.1 PROJECT PLANNING AND MANAGEMENT

The project was developed over a period of approximately three months. Although consideration of the research problem and hypothesis began about one month earlier, the effective working period was limited to three months. Within this timeframe, the theoretical and practical components of the project had to be completed.

Due to the limited time, the work was divided to proceed in parallel. On the one hand, the written component was developed progressively throughout the three-month period. As the project evolved and its overall approach became clearer, the report was reviewed. It was rewritten multiple times. This was done to ensure that it accurately reflected the current state of the work.

On the other hand, the practical component was structured into distinct phases. Since the project lacked direct references or established precedents, organizing the work into phases was necessary to define a clear methodology, manage uncertainty, and ensure that all objectives were completed within the established timeframe.

- **Text research & concept definition (Weeks 1–2):** This phase represented the initial stage of the project. Its primary objective was to develop a plausible concept based on a clearly identified problem. Since an analysis of the visual landscape had already been conducted, the remaining task was to formulate ideas that directly addressed the issues that had been identified.

The outcome of this phase is presented in the [1.2](#) section, where the problem is formally defined and the development of a functional tool for visual creation is proposed.

- **Data structuring & how to create the tool (Weeks 3–8):** This phase proved to be the most problematic and challenging of the entire project. The objective was to create

a tool that integrated artificial intelligence into TouchDesigner; however, at the outset, there was no clear methodological approach for achieving this integration. As explained in training the LLM section 3.2, several strategies were explored to determine how LLM-based models could be trained and effectively incorporated into the TouchDesigner environment.

Over the course of several weeks, different possibilities were tested and evaluated. Ultimately, it was determined that the most suitable solution was to use LOPs, training the agents with HTML files as their primary knowledge source. Reaching this decision required extensive experimentation and analysis, and the process took approximately two weeks before a clear direction could be established.

Once the roadmap had been defined, a significant amount of time was dedicated to learning the fundamentals of LOPs. This included understanding how to install the system, how agents function, how each operator works, and how to design an effective workflow. This learning phase involved extensive testing and experimentation and lasted an additional couple of weeks before the actual construction of the system could begin.

- **Creation of the tool (Weeks 9-12):** This phase represented the final stage of the project and was likely the one that would have required the most time under different circumstances. Due to the project deadline, only four weeks were available to begin configuring the TouchDesigner network in combination with the LLM models. Given the complexity and broad scope of the proposed tool, this phase could have extended significantly longer, as the system offers substantial potential for further development and refinement.

Within the limited timeframe, the result was a preliminary version of the tool that was relatively simple and not yet fully automated. Nevertheless, during these four weeks, it was possible to successfully generate visuals centered around a shader-based aesthetic, drawing on color palettes derived from different artists. Although the implementation remained at an early stage, this phase demonstrated the feasibility of the approach and laid the groundwork for future improvements and expansion.

4.2 ECONOMIC STUDY OF THE WORK PERFORMED

The project lasted approximately two and a half months and was completed by two people. During this period, they designed and developed a software tool that enables the integration of Large Language Models (LLMs) into TouchDesigner, allowing for their use in creative and interactive environments.

Regarding direct economic costs, the project was completed on a very limited budget, primarily consisting of software subscription fees.

- Cursor: 15€ per month
- DotSimulate: 9€ per month.

Given the project's total duration of two and a half months, the overall subscription costs were as follows in figure x:

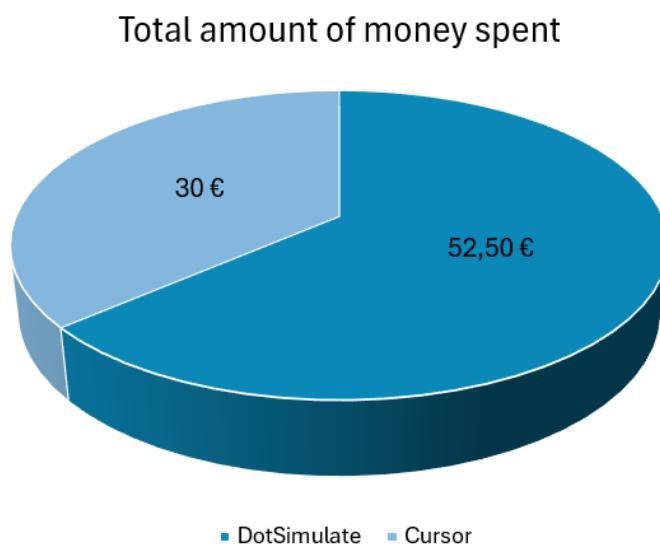


Figure 12: Graphic of the amount of money spent on the project.

Additionally, two Gemini API keys were used during the development process. These were obtained free of charge, so they did not generate any additional costs.

No expenses related to hardware, infrastructure, or additional software licenses were incurred. The primary contributions to the project were the time, expertise, and technical knowledge provided by the two developers. These contributions were

not monetized in this economic analysis because the project was conducted in an experimental, research-oriented context.

In conclusion, this project demonstrates that a functional tool integrating TouchDesigner with LLM-based systems can be developed at a very low cost by relying primarily on accessible software solutions and free API services.

5

CONCLUSIONS

5.1 conclusions

A

TIPS AND GUIDES FOR THE SETUP

A.1 HOW TO CONNECT AN AGENT WITH MEMORY

To interact with an agent, you typically use the addMessage operator, which sends a message to the agent and receives a response as seen in Figure 13. This works well for single exchanges: you ask something, the agent replies, and the interaction ends there. However, addMessage does not support memory, so it cannot maintain an ongoing conversation. Each new message is treated as an isolated request.

If you want to create a continuous dialogue with an agent, one in which the agent remembers previous messages, you should use the agentSession operator instead. As shown in Figure 14, this operator allows you to establish a session that preserves conversational context. To use it, open the operator, go to the Agent Session section, and attach the agent you want to interact with. Once connected, the agent will be able to maintain memory throughout the session.

Additionally, you can enhance the experience by connecting a chatViewer element to the agentSession. This provides a more intuitive, user-friendly interface for viewing and conducting the conversation.

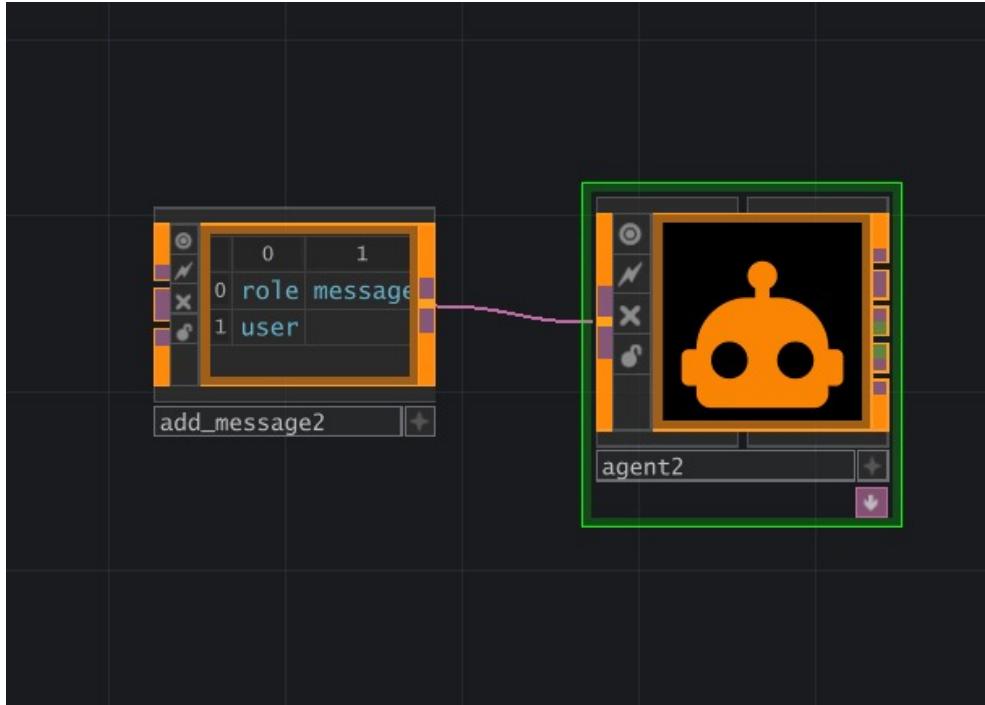


Figure 13: Connection between the operator addMessage and an Agent in Touch Designer

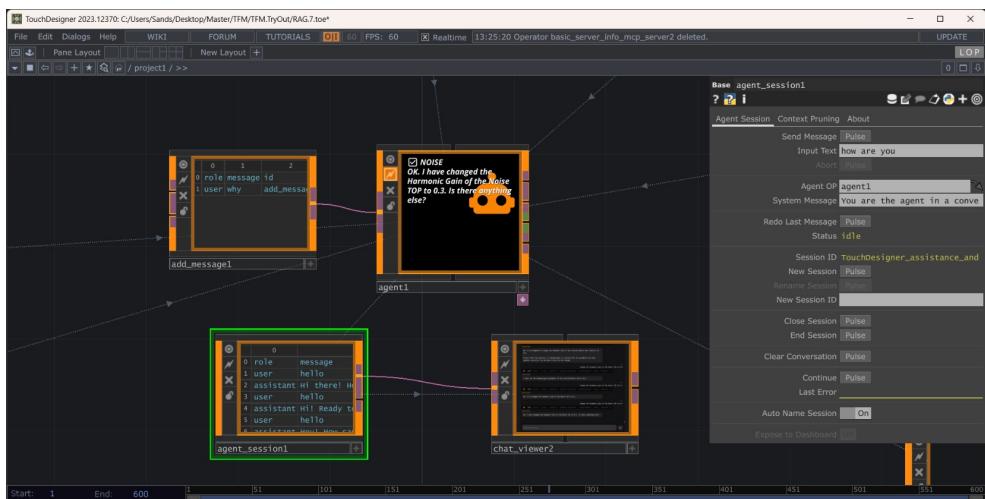


Figure 14: Connection between the operator agentSession and an Agent in Touch Designer

A.2 HOW TO INTRODUCE YOUR INFORMATION DOCS TO THE AGENT

The agents within LOPs have a limited ability to operate independently, but the real strength of the system lies in its capacity to train an LLM model using custom documents. To achieve this, the following steps must be followed, as shown in the figure 15:

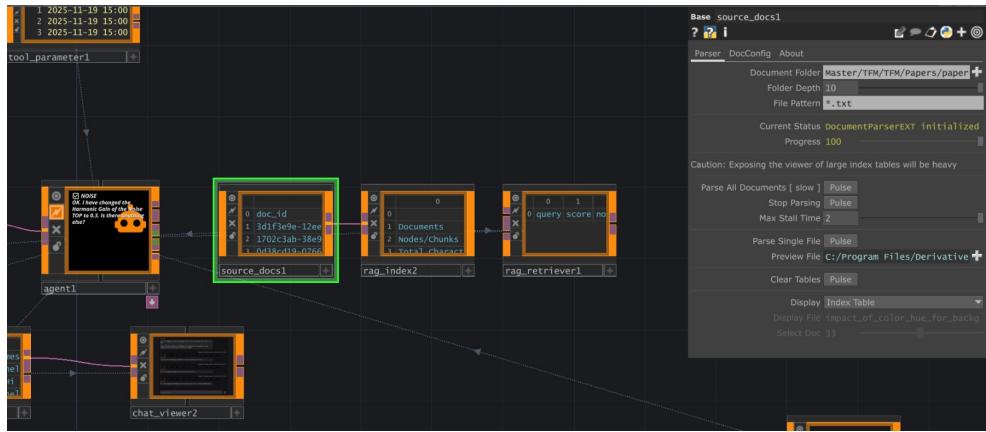


Figure 15: Workflow for the connection of personal documentation to make the agent learn based in the LLM

- **Create a source_docs operator:** This operator can receive files in PDF, TXT, Markdown, Notes, or code formats. Essentially, it serves as the raw knowledge base from which the agent will learn.
- **Add a rag_index operator:** LLM models cannot directly search through text; instead, they rely on metadata to retrieve information. The rag_index processes the provided documents by splitting the text into chunks, generating embeddings for each chunk, and constructing a vector database. This database allows the system to efficiently access the relevant portions of the documentation. The operator then stores the metadata associated with these embeddings.
- **Use a RAG retriever operator:** This component is responsible for receiving the agent's query and returning the most relevant information. It takes in the agent's question, instructions, and conversation history, and from this input, it retrieves the 3–5 most relevant text fragments from the documents provided via source_docs. These fragments are then

automatically injected into the agent's prompt, enabling it to respond accurately and contextually.

This workflow ensures that the agent can use custom knowledge effectively, grounding its responses in the documentation provided during training. As seen in figure 16, all these external tools have to be connected to the agent.

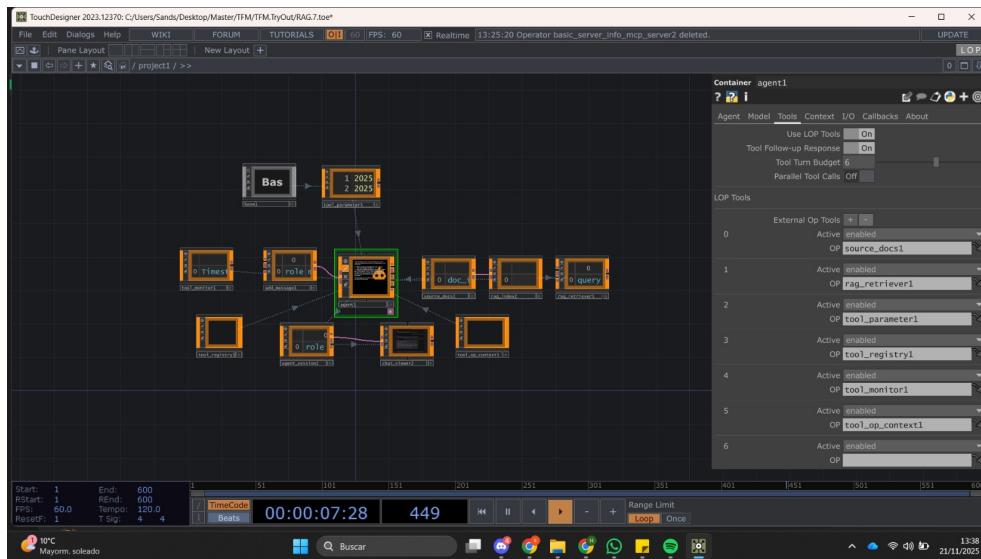


Figure 16: External tools connected to an agent

A.3 PROBLEM WITH RAG INDEX CHUNKS

One of the problems encountered during the assembly of this project has been the size of the chunks used by the LOPS RAG index. The previous section A.2 discussed how to make an agent learn from its own documents. In this case, the problem occurs within the Rag_index operator. Once the Source_docs has been configured, Rag_index is connected to it. This operator has the interface shown in the figure 17. When you click the “create index” button, a relatively common error may occur. The indexing process begins normally, but after a few moments, an error message suddenly appears on the screen, as shown in the figure 18 .

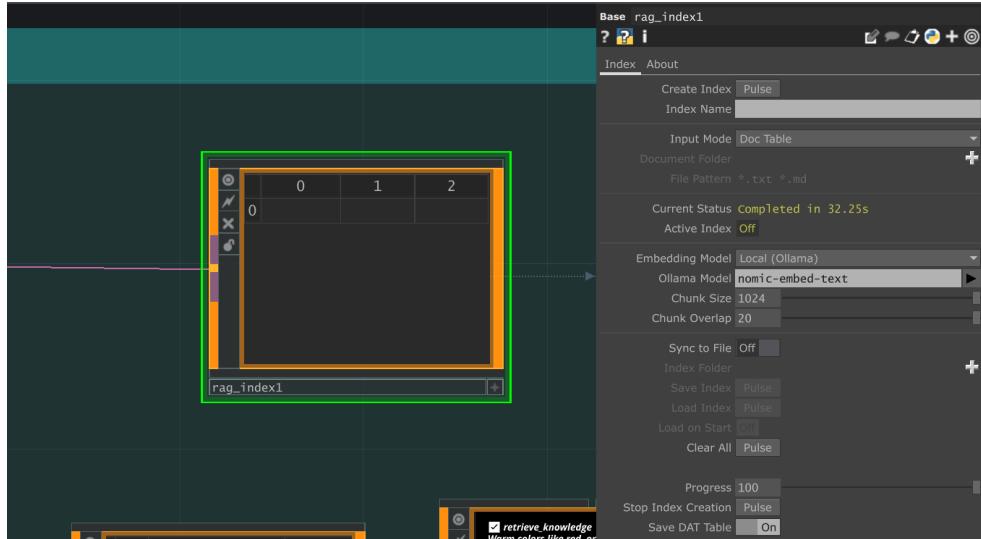


Figure 17: Parameters of the rag_index operator

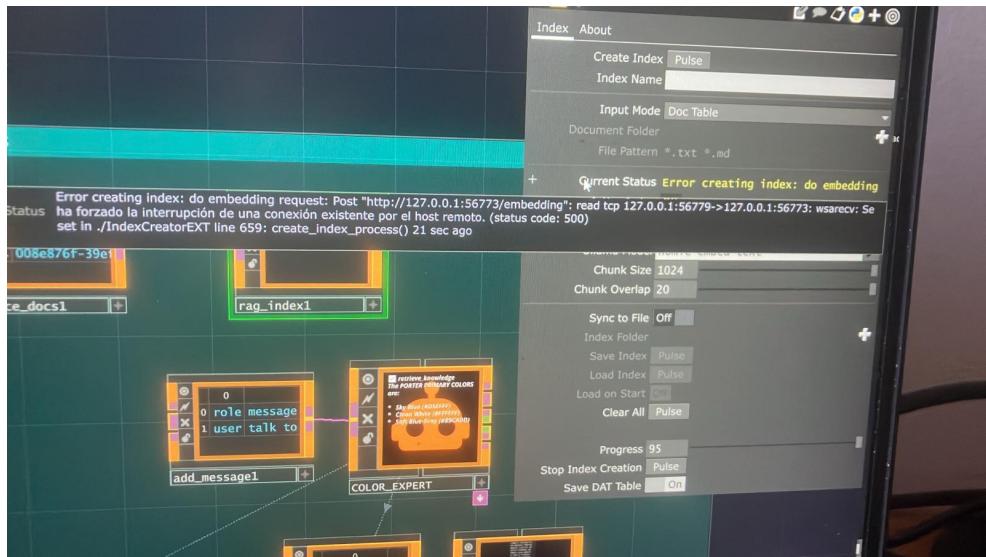


Figure 18: Error creating index in rag_index

This error message suggests a problem related to TCP ports, but in reality, it is caused by chunks that are too large for the system to process. Chunks are units of information divided into manageable fragments, commonly used in computing to handle large files efficiently. They play a key role in how data is organized, segmented, and processed. In this case, oversized chunks can overload the system, causing the indexing process to fail.

There are two possible solutions to address this issue:

- **Reduce the chunk size:** This is the simplest approach, although it does not guarantee success in every case. In the chunk_size field, you can decrease the size of each chunk so that the system can handle them more easily. A practical starting value is 256, which often resolves the issue by making the chunks small enough for the indexer to process without errors.
- **Modify the IndexCreatorEXT operator inside the Rag_index operator:** This approach provides more control over the indexing process. As seen in Figure 19, rag_index operator begins with the documents_table node, which stores the raw documents received by the system. This data then passes to stats_table and index_info_table, which record metadata such as the number of chunks, their average size, and the index ID. The in1 node receives the documents coming from the external source_docs, while IndexCreatorEXT oversees the entire indexing operation by calling Ollama to generate the embeddings. After that, a switch operator determines which view should be displayed, and finally, disp outputs the result of the processed index.

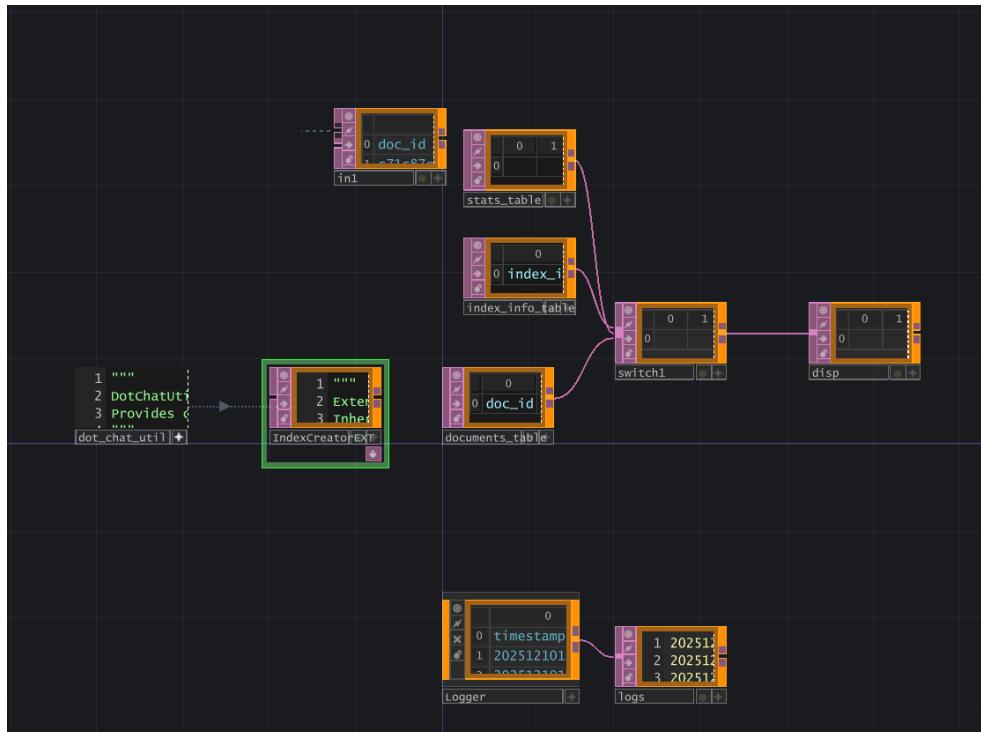
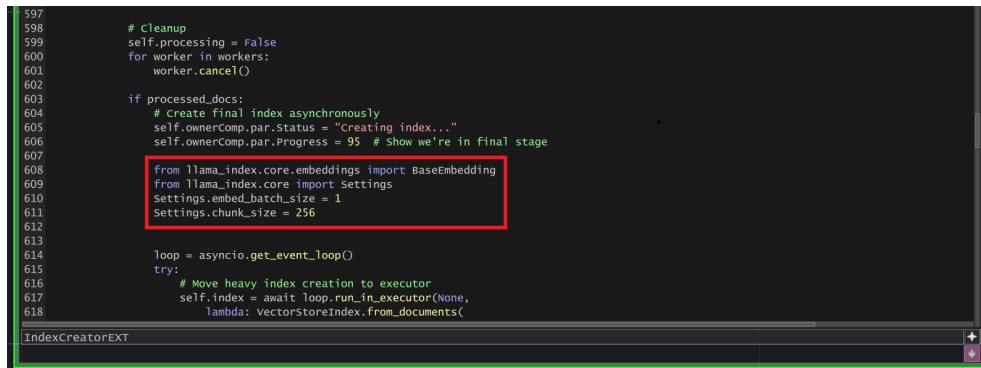


Figure 19: Structure inside of the Rag_index.

To fix this error, you need to access the IndexCreatorEXT operator. Inside it, you will find a block of Python code that controls how the embeddings are generated. The solution requires modifying this code directly.

Navigate to line 608, and, as shown in the figure 20, add the following lines:

```
from llama_index.core.embeddings import BaseEmbedding
from llama_index.core import Settings
Settings.embed_batch_size = 1
Settings.chunk_size = 256
```



```

597     # Cleanup
598     self._processing = False
599     for worker in workers:
600         worker.cancel()
601
602     if processed_docs:
603         # Create final index asynchronously
604         self.ownerComp.par.Status = "Creating index..."
605         self.ownerComp.par.Progress = 95 # Show we're in final stage
606
607     from llama_index.core.embeddings import BaseEmbedding
608     from llama_index.core import Settings
609     Settings.embed_batch_size = 1
610     Settings.chunk_size = 256
611
612
613     loop = asyncio.get_event_loop()
614     try:
615         # Move heavy index creation to executor
616         self._index = await loop.run_in_executor(None,
617                                               lambda: VectorStoreIndex.from_documents(
618
IndexCreatorEXT

```

Figure 20: Lines added to fix the error.

These settings reduce the number of elements the computer processes at once by lowering both the batch size and the chunk size. As a result, the system becomes much less likely to overload during indexing, helping prevent the error and allowing the RAG index to be created successfully.

B

CODES USED FOR THE PROJECT

B.1 PAPERS_CLEAN.PY

Listing 1: Python code to clean problematic characters

```
import pandas as pd
import re

df = pd.read_csv("Papers_Sumary.csv")

def clean_text(text):
    if pd.isna(text):
        return ""

    # Remove references like [number] or (year)
    text = re.sub(r'\[\d+\]|\(\d{4}\)', '', text)

    # Replace multiple spaces with one
    text = re.sub(r'\s+', ' ', text)

    # Remove special characters (ASCII-safe)
    text = re.sub(r'["\-\.\"]', '', text)

    # Trim and convert to lowercase
    text = text.strip().lower()
    return text

df["title"] = df["title"].apply(clean_text)
df["summary"] = df["summary"].apply(clean_text)
df["keywords"] = df["keywords"].apply(clean_text)

df.to_csv("papers_clean.csv", index=False)
print("Clean CSV saved as papers_clean.csv")
```

B.2 PAPERSEMBEDDING.PY

Listing 2: Python code to do the embeddings

```

import pandas as pd
from sentence_transformers import
    SentenceTransformer
import chromadb

df = pd.read_csv("papers_clean.csv")
for col in ["summary", "keywords"]:
    if col not in df.columns:
        df[col] = ""
df.fillna("", inplace=True)
df["text"] = df["title"] + ". " + df[""
    summary"] + " " + df["keywords"]

texts = df["text"].tolist()
metadata = df[["title", "authors", "year",
    "keywords"]].to_dict(orient="records")

# Generate embeddings
model = SentenceTransformer("all-MiniLM-L6-
    v2")
embs = model.encode(texts, show_progress_bar
    =len(texts)>50, convert_to_numpy=True,
    batch_size=32)

# Create clients
client = chromadb.PersistentClient(path="./
    chroma_db")
collection = client.get_or_create_collection
    (name="papers_color")

# Insert documents of the files
collection.add(
    documents=texts,
    embeddings=embs.tolist(),
    metadata=metadata,
    ids=[f"doc_{i}" for i in range(len(texts))]
    )

print("Vectorial base created in ./chroma_db
    ")

```

```
q_emb = model.encode([query])[0].tolist()
res = collection.query(query_embeddings=[q_emb], n_results=3, include=["documents", "metadatas"])

print("\nResults:")
for doc, meta in zip(res["documents"][0], res["metadata"][0]):
    print("Title:", meta["title"])
    print("Authors:", meta.get("authors"))
    print("Year:", meta.get("year"))
    print("Text (start):", doc[:200], "...\\n")
```

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