Explaining Genetic Programming Trees using Large Language Models

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Abstract-Genetic programming (GP) has the potential to generate explainable results, especially when used for dimensionality reduction. In this research, we investigate the potential of leveraging eXplainable AI (XAI) and large language models (LLMs) like ChatGPT to improve the interpretability of GPbased non-linear dimensionality reduction. Our study introduces a novel XAI dashboard named GP4NLDR, the first approach to combine state-of-the-art GP with an LLM-powered chatbot to provide comprehensive, user-centred explanations. We showcase the system's ability to provide intuitive and insightful narratives on high-dimensional data reduction processes through case studies. Our study highlights the importance of prompt engineering in eliciting accurate and pertinent responses from LLMs. We also address important considerations around data privacy, hallucinatory outputs, and the rapid advancements in generative AI. Our findings demonstrate its potential in advancing the explainability of GP algorithms. This opens the door for future research into explaining GP models with LLMs.

Index Terms—Genetic Programming, Non-Linear Dimensionality Reduction, Explainable AI, ChatGPT, Large Language Models

I. INTRODUCTION

G ENETIC programming (GP) is a powerful evolutionary computation technique that evolves computer programs to solve complex tasks. Its versatility and ability to automatically discover model structure make it an attractive choice for solving many problems. GP is capable of producing functional mathematical mappings with good predictive accuracy. These symbolic mappings (trees) are a promising approach for enabling eXplainable Artificial Intelligence (XAI) [1].

The field of XAI is at the forefront of current research. It is crucial within sectors such as medical diagnosis and financial risk assessments, where explainability is required to gain trust among stakeholders [2]–[4]. However, even with the symbolic nature of GP, understanding the semantics of a GP model/tree or the meaning of individual features may require expert domain knowledge. Even understanding the functionality of the evolutionary process may lie beyond the comprehension of end-users.

The term *end-users* is deliberately vague. Different audiences need wildly different explanations, personalised to their background and requirements. Ribera [5] highlighted the importance of approaching XAI from a *user-centred* perspective. They categorised the targeted audience into three broad groups: *developers and AI researchers, domain experts*, and *lay users*. They showed that explanations are multifaceted, requiring different explanations for every user group. For example, vocabulary needs to be adapted to match the comprehension level of each group, by omitting technical terms for lay users and integrating domain-specific terminology when engaging with experts. Humans are also social creatures, who learn through conversation [6]. An explanation delivered through a *conversational exchange* would allow users to directly request answers suited to their own domain knowledge and technical background, greatly improving the explanation quality.

The proliferation of large language models (LLMs) such as OpenAI's ChatGPT has powered a notable surge in chatbot development, facilitating conversational question-and-answering over a broad range of domains. Therefore, this study introduces an AI-driven chatbot to explain the functionality of GP models/trees. Leveraging LLMs in this way capitalises on a wealth of domain knowledge, aiding in understanding results. When responses do not align with the user's level of understanding, they may seek further clarification through conversation. The inherent nature of the LLMs enables users from diverse backgrounds to pose questions around presented findings by using language, vocabulary, and grammar of their preference. Existing studies highlight the multilingual capabilities of LLMs [7] and their comprehension in understanding questions containing grammatical or typographical errors [8].

The versatility of genetic programming deems it applicable to a plethora of tasks in real-world applications, including but not limited to symbolic regression [9], job scheduling [10], classification [11], and feature selection [12]. This paper focuses specifically on improving the explainability of Genetic Programming for Nonlinear Dimensionality Reduction (GP-NLDR) methods. Modern datasets often have thousands or tens of thousands of features, which can only be processed by extremely complex and expensive machine learning approaches [13]–[17]. NLDR methods can greatly reduce the dimensionality (number of features) of a dataset, making the data easier to process and understand. GP-NLDR, unlike traditional NLDR methods, has shown promise in performing explainable NLDR, where the reduced dimensions (embedding) can be directly understood in the context of the original features [17]– [20]. In this paradigm, each new dimension in the embedding is represented by a single GP tree, where the tree takes a subset of original features as its inputs (leaves) and produces a single output (embedding dimension). Despite continued research,

This work was supported by the University Research Fund at Te Herenga Waka–Victoria University of Wellington under grant number 410128/4223.

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GP-NLDR can still produce overly complex trees, which are not explainable to non-experts.

This study proposes GP4NLDR, a web-based dashboard that utilises an LLM-powered chatbot to explain GP-NLDR trees. We opt for a web-based architecture to enhance the accessibility of our research to the diverse audience identified in our study. Leveraging an intuitive graphical user interface with rich visualisations simplifies interaction with the system, contrasting with alternative delivery methods such as command-line processes and code libraries. While we constrain our study's scope to GP-NLDR, our framework is applicable to many GP applications, laying the groundwork for significant advances in explainable GP.

Major Contributions

- This study explores the feasibility of using LLMs such as ChatGPT to provide human-like explainability of GP expressions. It contributes to combining the fields of evolutionary computation and generative AI, a notably scarce approach in existing literature. We demonstrate that our proposed methodology can be extended to other applications of GP.
- Previous work [19]–[21] has presented state-of-the-art techniques for GP-NLDR. This study makes this research accessible by making our custom-built online system GP4NLDR¹ publicly available. The platform allows users to learn about GP-NLDR by running it on datasets using different fitness functions and run parameters. The GP expressions and trees are viewable together with run results.
- Our proposed approach incorporates LLM-driven conversational interactions via a chatbot natural language interface. The chatbot is customised through prompt engineering and retrieval augmented generation to help strengthen the understanding of tree expressions and output. The GP4NLDR software interface allows the use of the chatbot with self-generated examples or through pre-loaded case studies.
- Finally, we contribute to the growing body of research highlighting limitations in using LLMs and the impact of hallucinations on XAI, with a unique perspective on these issues within explainable GP.

II. RELATED WORK ON XAI

Recent years have seen the emergence of diverse XAI techniques fostering the explainability of black-box models. Comprehensive analyses [22], [23] present the complexities and nuances of these numerous XAI strategies across broad interdisciplinary domains. Our focus is not to re-visit the extensive list already presented by the authors, but rather highlight some as illustrative examples supporting the goal of our research. In predictive machine learning models, approaches such as SHAP [24] and LIME [25] provide insights for local and global explainability; Anchors [26] provides a set of rules under which predictions still hold with confidence;

and DiCE [27] is used in modelling *what-if* counterfactuals. Previous studies demonstrate their use in domains such as healthcare [28]–[30] and education [31], [32]. However, these approaches target model developers capable of translating the interpretations into lay terms for communicating to stakeholders. Prior studies [33]–[35] have developed chatbots for endusers to engage in conversational exchanges, enhancing their understanding of these XAI tools' output. However, no studies have utilised groundbreaking large language models such as ChatGPT within this domain.

There is extensive literature that seeks to improve the explainability of GP [1] through approaches such as building smaller trees with bloat control [36] or using fewer features [37]. However, this poses the same challenges with XAI tools previously discussed, where the output is targeted towards those knowledgeable in these concepts, failing to enable XAI from a *user-centred* perspective which caters to a broader, non-expert audience.

Communicating the explainability of AI systems has also been explored from a social sciences standpoint. Previous studies [6] highlight how the field of XAI may benefit from incorporating insights from philosophy, cognitive psychology/science, and social psychology to understand how humans define, generate, and evaluate explanations. Their work highlights how XAI may benefit from understanding how decisions are explained to humans and how humans articulate decisions to each other.

The role of natural language in generating explanations has been surveyed in prior studies [38]. The authors concluded only a handful of recent XAI approaches either considered natural language explanations for end-users or implemented a method capable of generating such explanations. A recent review of works in the emerging field of interpreting LLMs and using them for explanation highlights LLMs possess the opportunity to redefine interpretability across a wide range of applications [39]. A recent study [40] proposes leveraging large language models for the automated analysis of optimisation algorithms within a web-based tool [41] for the generation of search trajectory networks . They highlight how this application of LLMs may enhance the user experience of the tool and bridge the knowledge gap for those without prior understanding of the application. However, no previous work has been identified using natural language chatbots to delve deeper into explaining GP expressions, nor its use in the field of NLDR. Several notable context-based chatbot implementations have recently emerged in other domains, leveraging similar technologies to those implemented in our study. Aisha [42], a library chatbot, uses prompt engineering with a Chroma vector database together with LangChain and ChatGPT to deliver reference and support services to students and faculty through a Streamlit interface. In the medical domain, accGPT [43] is a ChatGPT-based chatbot that provides personalised imaging recommendations supporting clinical decision-making. It leverages LlamaIndex to access information within the American College of Radiology documentation.



Fig. 1: Overview of GP4NLDR Architecture

III. METHODOLOGY

In this study, we used Streamlit², an open-source Python framework, to build an online web-based application GP4NLDR³. The application incorporates existing GP-NLDR code bases from prior works in the field [19]-[21] to perform the NLDR. The process outputs one GP tree for each dimension of the new embedding, together with performance metrics. We then introduce the use of generative pretrained transformer (GPT) LLMs to facilitate conversational question answering [44], to greatly improve the explainability of the trees found by GP-NLDR. We further developed our approach by incorporating intelligent prompt engineering and pre-initialising the LLM with additional knowledge from existing literature through the use of retrieval augmented generation, which guides it to deliver focused and targeted on-topic responses. We utilise the popular Langchain [45] framework to streamline the integration of LLMs and the workflow components.

Fig. 1 depicts an overview of the GP4NLDR architecture. The system provides a facility to run the NLDR-GP process on a given dataset or view pre-loaded examples for quick use. After results are generated, the chat feature can be initialised. A written summary of the process is presented as interpreted by the LLM. Then, further dialogue conversations with the chatbot can commence. We elaborate on these stages more comprehensively in the following subsections.

A. GP4NLDR System

Fig. 2 depicts the GP4NLDR system showing parameter options and dataset information. For ease of understanding the dataset, the original values are presented, along with the scaled data⁴ used in the dimensionality reduction process. We now discuss the design of each part of the system in turn.

1) Parameter Options for the NLDR process:

- Population Size: the number of individuals in the population. A larger size may enhance the learning ability but increases computational complexity. A smaller size may lead to insufficient diversity and premature convergence.
- Number of Generations: how many iterations of the algorithm to perform. It requires a balance between allowing the population to evolve towards an optimal solution and avoiding extended computational costs. Monitoring convergence on the fitness plot may help determine a suitable value.
- Final Dimensions: how many dimensions the embedding should contain (i.e. the number of GP trees). Prior knowledge of the data domain or task requirements determines this number. Alternatively, for visualisation of the dataset, three or fewer dimensions would be chosen.
- Fitness: The fitness function measures the quality of the NLDR solution and helps guide the evolutionary process towards a better solution. Available options include GP-MaL [19], GP-Mal-2 (the first objective of [20]), UMAP Cost [21] and NRMSE [21].
- Bloat Control: optional techniques to help reduce the size of GP trees to prevent unnecessary growth, improving

⁴Data scaled using Scikit-learn's MinMaxScaler.

²https://streamlit.io/

³Hosted on Streamlit Community Cloud https://gp4nldr.streamlit.app/

Home		
Examples		
Developed by Paula Maddigan for Victoria University of Welling	gton (?)
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Datasets courtesy of UCI 🕐		

GP4NLDR

4

Using Genetic Programming for Non-Linear Dimensionality Reduction Interpreted by ChatGPT

Wine	
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Original Dataset Scaled Datase

Color intensity (f9	Proanthocyanins (f8)	Nonflavanoid phenols (f7)	Flavanoids (f6)	Total phenols (f5)	Magnesium (f4)	Alcalinity of ash (f3)	Ash (f2)	Malic acid (f1)	Alcohol (f0)	class
5.64	2.29	0.28	3.06	2.8	127	15.6	2.43	1.71	14.23	1
4.38	1.28	0.26	2.76	2.65	100	11.2	2.14	1.78	13.2	1
5.68	2.81	0.3	3.24	2.8	101	18.6	2.67	2.36	13.16	1
7.8	2.18	0.24	3.49	3.85	113	16.8	2.5	1.95	14.37	1
4.32	1.82	0.39	2.69	2.8	118	21	2.87	2.59	13.24	1
6.75	1.97	0.34	3.39	3.27	112	15.2	2.45	1.76	14.2	1
5.25	1.98	0.3	2.52	2.5	96	14.6	2.45	1.87	14.39	1
5.0	1.25	0.31	2.51	2.6	121	17.6	2.61	2.15	14.06	1
5.	1.98	0.29	2.98	2.8	97	14	2.17	1.64	14.83	1
7.2	1.85	0.22	3.15	2.98	98	16	2.27	1.35	13.86	1
5.7	2.38	0.22	3.32	2.95	105	18	2.3	2.16	14.1	1
:	1.57	0.26	2.43	2.2	95	16.8	2.32	1.48	14.12	1
5.	1.81	0.29	2.76	2.6	89	16	2.41	1.73	13.75	1
5.4	2.81	0.43	3.69	3.1	91	11.4	2.39	1.73	14.75	1
7.	2.96	0.29	3.64	3.3	102	12	2.38	1.87	14.38	1
7.	1.46	0.3	2.91	2.85	112	17.2	2.7	1.81	13.63	1
6.	1.97	0.33	3.14	2.8	120	20	2.72	1.92	14.3	1
6.	1.72	0.4	3.4	2.95	115	20	2.62	1.57	13.83	1
8.	1.86	0.32	3.93	3.3	108	16.5	2.48	1.59	14.19	1

Fig. 2: GP4NLDR System

performance and tree interpretability. Options include: (1) lexicographic [46] — a parsimony pressure method that prefers smaller trees when fitness values are equal; (2) double tournament [47] — uses two tournaments: one for fitness and one for size, with the selection of which tournament is run first and the probability that a smaller individual is chosen over a larger more complex one; and (3) Tarpeian [48] — which penalises large individuals during evolution according to a provided probability.

2) Display of NLDR Results: On completion of the GP-NLDR process, the results are displayed for analysis. A summary of parameters is noted, followed by tree expressions and visualisations for each new dimension. The raw embedding result is presented alongside a plot depicting fitness per generation. If the embedding dimensionality is 3D or lower, a visualisation of the embedding is provided: either as a 3-D rotational plot, a 2-D scatter plot, or a 1-D bar graph. A random forest classifier [49] implemented in Scikit-Learn [50] with 10-fold cross-validation is also used to provide an estimated accuracy for both the original dataset and that of the new embedding, as a proxy of embedding quality.

3) Chatbot: The chat feature is initialised upon entering a valid OpenAI API key, selecting an LLM (e.g. GPT-3.5 or GPT-4) for conversation, and confirming the approximate word limit for responses. The word limit is set to a default of 80 words. Too few words may return insufficient explanations. Excess words may prolong response times and introduce verbosity, repetition, or tangential answers.

The pre-engineered prompt (discussed further in Section III-D) and initial question "Provide an exciting summary of the results" are submitted to the LLM. The LLM returns a brief overview of the results as a starting answer for the conversation. Then, two-way conversational question-andanswering with memory retention begins, utilising retrieval augmented generation when required. At any stage, the results and chat history may be downloaded, allowing for reloading at a later point in time.

4) Pre-loaded Examples: The system provides exploration of previously generated GP-NLDR evolutionary runs, including the case studies presented in this work. The chat feature is available within each example to help further interpret the output. This facility allows for the reproducibility of our research for each GP-NLDR case study presented. LLMs are deterministic models, fundamentally generating the same outputs for the same inputs. Nevertheless, as their responses are probabilistic, they may appear non-deterministic. Therefore, it may not be feasible to achieve identical explanations even though the input prompt remains unchanged. If desired, previously generated results from user experiments may also be reloaded here for further analysis.

B. Large Language Models

The rapid advancement in LLMs throughout this research project opened avenues to investigate the capabilities of both existing and emerging models, including open-source solutions. Following the evaluation of the performance and accessibility for the task at hand⁵, OpenAI's ChatGPT-3.5 model (gpt-3.5-turbo) was adopted as a foundation for the development of GP4NLDR's chat feature. This Chat Generative Pre-trained Transformer model 3.5 is based on the transformer deep learning architecture. It is designed to generate humanlike text in response to input questions. This state-of-the-art language model excels at natural language processing and conversational exchanges.

We used the Python openai library to facilitate an authenticated connection to the OpenAI models with requests submitted via the API endpoint. We refrained from explicitly including the model version suffix⁶ allowing us to take advantage of the continuous model upgrades, therefore insuring we provided the safest and most capable model version. OpenAI regularly upgrade model versions, thus for the long-term viability of our research it was important to mitigate deprecation issues stemming from tying the research to specific model versions. Additional options are provided within the chatbot for using the legacy model GPT-3 and the most recent addition, GPT-4. We use the default LLM model parameter settings, with the temperature set to zero to encourage response consistency. To access the models in the chat function, a valid OpenAI API key is required⁷.

C. Retrieval Augmented Generation

At the time of writing, ChatGPT-3.5 was trained on data up until the end of September 2021. Consequently, with some research information beyond its reach or in publicly unavailable studies, many recent concepts in the evolving GP field are unknown to the model. Retrieval augmented generation (RAG) [51] is a technique to address this limitation. RAG builds a vector store/database of vector embeddings from relevant documents. By performing vector searching using similarity metrics, relevant information is extracted and injected as contextual background information into the user's prompt. This helps fill knowledge gaps in the model and provide it with recent insights, and presents a cost-effective and dynamic alternative to pre-training or fine-tuning models.

The GP4NLDR processor centres on the articles referenced in previous studies [19]-[21], but can be easily extended to other methods. A vector store of these papers was constructed by generating vector embeddings of the documents, and then made available to the application. A computationally expensive vector database⁸ was not needed for this use case, and so we opted to use FAISS [52], Facebook's AI Similarity Search vector index library⁹. Given a fixed number of stored articles, with no requirement to add additional files or update existing ones, FAISS is a very efficient and suitable option. The vector store is integrated into the application chat feature for OpenAI models. During conversational chatting, user-provided questions are analysed against a pre-defined set of keywords: gp-mal, gpmal, gpmal2, gp-mal2, gp-mal-2, tarp, lexi, tourn, umap, nrmse¹⁰. In our initial prototypes (without a vector store), using these keywords often returned responses of limited usefulness, even on occasion provoking hallucinations, as these abbreviations are less prevalent within the model training data. When questioned about these keywords in the context of GP through the ChatGPT OpenAI interface, the LLM did not consistently provide accurate responses. Hence, should these keywords be present, RAG is activated, and the FAISS vector index is queried to fetch relevant background information. Upon retrieval, the information is injected into the prompt. For queries outside the keyword list, it is expected that the model maintains enough background knowledge and the prompt is sufficient to acquire an informative response to the query. This process can be seen within Fig. 1.

D. Prompt Engineering

Careful consideration was given to our prompt development to elicit informative and consistently reliable responses. Fig. 3 shows the entire initial prompt using an example from the Wine Case Study presented later in our results. Bolded text represents the automatic injection of content from the specific example.

- Fig. 3(a) establishes the context for the discussion, directing the LLM to focus on genetic programming and non-linear dimensionality reduction.
- The fitness function GP-MaL-2 is not explicitly mentioned within the publications in the vector store. Consequently, we define it explicitly in the prompt.
- Fig. 3(c) explains the operators used in the GP algorithm.
- Fig. 3(d) informs the LLM with the name of the dataset and a summary of the parameters used.
- The dataset features are listed in Fig. 3(e). Should the • feature list exceed 40, we replace the feature list with the text **f0 to fn-1** (as a dataset with **n** features). This tweak avoids exceeding the token limit for large datasets, such as COIL20, with more than 1000 features.
- Fig. 3(f) provides the LLM with the dataset dimension specifications and resulting expressions.
- Providing the classification accuracy of the original and • reduced space in Fig. 3(g) informs the LLM how well the NLDR process performed.
- Specifying the response word count when initialising the LLM allows flexibility in token usage during chatting, with the allowance specified within the prompt in Fig. 3(h).
- Fig. 3(i) guides the LLM further in the expectations for response content, ensuring that information in the prompt is not repeated.
- · Should the question contain keywords, background information is retrieved from the vector store and injected in Fig. 3(j).

⁵The evaluation process lies outside the contribution of this work and as such is not presented.

⁶For example gpt-3.5-turbo-0613

⁷OpenAI API key available at https://openai.com/

⁸Vector databases provide create, read, update, and delete functionality. ⁹https://faiss.ai/

(a)	You are an expert on genetic programming (GP) and non-linear dimensionality reduction (NLDR). You are to discuss explaining the results of the GP expressions from NLDR.
(b)	GP-MaL evolves functional mappings from a high-dimensional space to a lower dimensional space through the use of interpretable trees. GP-MaL-2 is different from GP-MaL. It is the first objective of GP-MaL-0
(c)	The operators used in expressions are: x (multiply), ÷ (divide), max (maximum), min (minimum), + (add), — (subtract), ReLU (relu), sig (sigmoid), if (if), I—I (absolute subtract), I+I (absolute add).
(d)	The dataset is called Wine. Summary of parameters is Population Size: 100. Generations: 100.Fitness: GP-MaL. Bloat: Lexicographic Measure: Total Nodes Bucket Method: Direct Bucketing Bucket Value: 2.
(e)	The features are Alcohol (f0), Malic acid (f1), Ash (f2), Alcalinity of ash (f3), Magnesium (f4), Total phenols (f5), Flavanoids (f6), Nonflavanoid phenols (f7), Proanthocyanins (f8), Color intensity (f9), Hue (f10), OD280/OD315 of diluted wines (f11), Proline (f12).
(f)	Using GP the original 13 features have been reduced to new features in 2 dimensions, using the mapping expressions: Dim0=f6; Dim1=x(sig(ReLU(-(f12, f9))), ReLU(+(I-I(-0.5951, f9), max(-0.8216, f0))));
(g)	The accuracy of the original dataset is 0.9833. The accuracy of the new dimensional space is 0.9333.
(h)	Given the text of question, it is your job to answer that question in approximately 80 words.
(i)	There is no requirement for giving background to GP nor NLDR unless asked. The feature expressions are stated in the prompt and do not need restating in the answer. Use feature names rather than abreviations in the discussion. State the original features that are important in the GP expressons for each dimension, and those that are less important. Try to give an explanation about why the features are very important or less important in the context of the dataset.
(j)	For context here is background related to the question: {}
(k)	Human: Provide an exciting summary of the results. Al: The GP-MaL algorithm successfully reduced the original 13 features of the Wine dataset to 2 new dimensions. In the first dimension, the feature expression includes the Flavanoids (f6) feature, which suggests that this feature is important in distinguishing between different wine samples. In the second dimension, the expression includes the Proline (f12), Color intensity (f9), and Alcohol (f0) features, indicating their significance in the dataset. The other features are less important in the context of the dataset, as they are not included in the GP expressions.
(I)	Human: explain the 2nd dimension further Al:

• Fig. 3(1) shows an example initial conversational chat dialogue between the Human and the AI.

E. LangChain

LangChain [45] provides a modular framework for building applications powered by LLMs. The toolkit offers flexibility for integrating a diverse range of LLM model variants. Its versatile structure and functionality facilitated the integration of RAG into our application workflow. Preserving conversational memory within chatbots is paramount, and LangChain seamlessly facilitated the memory retention process.

F. GP4NLDR Evaluation

We demonstrate the capabilities of GP4NLDR and chat interactions over three case studies. The first two case studies are based on the Wine [53] and Dermatology [54] datasets, which contain meaningful feature names. The final case study uses the larger COIL-20 [55] dataset with 1024 features, lacking descriptive feature names. These examples demonstrate the system's behaviour across a range of different parameter options:

- A small dataset with 13 features and 178 instances through to a larger dataset of 1024 features and 1,440 instances.
- Different fitness functions (GP-MaL and GP-MaL-2).
- Reducing to two or three final dimensions.
- The use of lexicographic bloat control compared to no bloat control.
- From 100 generations through to 1000 generations.

Furthermore, these case studies investigate the calibre of chatbot responses in the following situations:

- Supplying descriptive feature names compared to sequentially allocating non-descriptive feature names, which may limit background information.
- Using keywords such as gpmal to engage with RAG.
- Subjective questioning, for instance, querying how good results are.
- Asking questions using terminology not identical but similar to feature names in the dataset.
- Probing the importance of features.
- The multilingual capabilities of LLMs.

In presenting the evaluation of each case study, we showcase subsections of the system results for illustration while depicting the complete interface in the Appendix. It is not feasible to demonstrate all possible parameter settings and scenarios. A curated selection has been chosen, emphasising those deemed most meaningful in showcasing our research results.

We pose questions in a manner that aligns with lay users. This demographic of users stand to benefit most from our study as they more typically rely on an intermediary party to translate existing ML explainability tools into summary text. The results are evaluated manually by comparing the correctness of the generated chatbot responses to the results depicted in the GP expression trees. In addition, we manually



Fig. 4: Wine Case Study Trees



Fig. 5: Wine Case Study Plots

evaluate and discuss the quality and accuracy of the responses to queries unrelated to the trees, which more specifically target dataset domain, GP, or NLDR questions. As the work presented in this study is the first to use LLMs to provide explanations of GP trees, difficultly lies in benchmarking our approach and providing measurable metrics of accuracy.

Our developed system¹¹ has been made publicly available for further experimentation and testing. The presented case study examples are viewable within the application, and may be further analysed using the chatbot. However we note, as touched on earlier, the generation of identically worded responses from subsequent questioning using the same prompt may not be achievable due to the inherent nature of LLMs. In this work we perceive this as an advantage, imparting a sense of personalised responses to the user rather than generic explanations.

IV. RESULTS

A. Wine Case Study

The Wine dataset¹² consists of 13 features and 178 instances detailing the chemical analysis of three types of Italian wine. The GP4NLDR process is run using the GP-MaL fitness function, reducing the Wine dataset to two dimensions after 100



Fig. 6: Wine Case Study Chat

generations using a population size of 100 and lexicographic bloat control. The first embedding dimension (GP tree) shown in Fig. 4(a) is a single node, representing the flavonoids feature. The second tree utilises the Proline, colour intensity, and alcohol features in Fig. 4(b). The fitness plot in Fig. 5 shows the function converges quickly, and the three classes are easily distinguishable within the 2D embedding plot.

Initiating the chatbot allows further investigation into the results. Including the feature names within the dataset structure feeds the LLM additional context when considering why some features are present in the new dimensional space while others remain absent. The overview initially generated is illustrated in Fig. 6(a). A brief discussion of the dimensionality reduction is given together with noting the features present in each dimension and deemed important. In Fig. 6(b), when asked to "explain the 2nd dimension further", the LLM expands the justification for the inclusion of each feature by providing definitions of the features and their relationship to the dataset. When questioning the LLM about a specific feature "what is hue?" in Fig. 6(c), the LLM gives an overview of its definition followed by its contribution to the results. In this example, hue was not part of the embedding and hence not deemed as important.

Supplying the accuracy of the embeddings when classified

¹¹https://gp4nldr.streamlit.app/

¹²https://archive.ics.uci.edu/dataset/109/wine



Fig. 7: Dermatology Case Study Plot

by a random forest algorithm may give somewhat subjective opinions from the LLM when asked if it is a "good" reduction. Fig. 6(d) shows the LLM believes this example is "effective" with "a slight decrease in accuracy" from 0.9833 to 0.9333.

B. Dermatology Case Study

The Dermatology dataset¹³ with 34 features classifies the type of erythematous-squamous disease into six classes (psoriasis, seborrheic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, and pityriasis rubra pilaris.) 12 features are clinical evaluations with a further 22 histopathological features from skin samples. There are 358 instances in total.

The GP4NLDR process is run using the GP-MaL-2 fitness function, reducing the Dermatology dataset to 3 dimensions over 200 generations using a population size of 100 and lexicographic bloat control. Fig. 7 illustrates the 3-D plot representing the reduced embedding. The three new dimensions each use between four and six features.

Once more, including the feature names within the dataset structure has assisted the chatbot in providing contextual conversational exchanges. When asked "*What if I am really old and itchy?*", the LLM maps the word "*old*" to the feature age and the word "*itchy*" to the feature itching. Fig. 8(a) shows it subsequently responds that neither of these features appears in the tree expressions and hence they have less influence or relevance in determining the type of skin condition.

In asking "Is GP-MaL better than GP-MaL-2?" in Fig. 8(b), the LLM notes it has not been supplied with information detailing specific comparisons between the two functions. This response may be perceived as uninformative; nonetheless, it shows that clever prompt engineering can help deter hallucinations. Throughout prompt development, experiments demonstrated the LLM's susceptibility to generating inaccurate information. Fig. 9 illustrates this concern by asking the question "Explain what GP-Mal is" through the online ChatGPT Web Interface¹⁴. ChatGPT invents the definition "Generative Pretrained Transformer for Malicious Software" and endeavours to discuss it convincingly. This example is testament to the mitigation of such hallucinatory outcomes by incorporating tailored prompt engineering.

14https://chat.openai.com/



whether GP-MaL is better than GP-MaL-2. The prompt only mentions that GP-MaL-2 is the first objective of GP-MaL-MO, but it does not provide any specific details or comparisons between the two approaches. Further information or analysis would be needed to make a comparison between GP-MaL and GP-MaL-2.

Fig. 8: Dermatology Case Study Chat





C. COIL-20 Case Study

The Columbia Object Image Library (COIL-20) dataset¹⁵ consists of gray-scale images of 20 objects. For each object, a photographed image was captured every 5 degrees as it was rotated 360 degrees on a motorised turntable, giving 72 images for each object. Each of these images represents one row in the dataset, giving 1,440 rows in total for the 20 objects. The original 128x128 pixel image size is cropped to 32x32 pixels, producing a 1024-dimensional feature example. The absence of feature names necessitates generically assigned attribute labels f0 to f1023. The full results in the supplementary material illustrate the results from the NLDR process, producing somewhat large trees. The fitness plot depicts the gradual improvement in the function over the 1000 generations. In reducing the dimensions from 1024 to 2, accuracy has decreased from 0.9868 to 0.6375.

¹³ https://archive.ics.uci.edu/dataset/33/dermatology

¹⁵https://www.cs.columbia.edu/CAVE/software/softlib/coil-20.php

What makes a feature important?

In the context of dimensionality reduction using GP, a feature is considered important if it has a significant impact on the mapping from the high-dimensional space to the lower dimensional space. This can be determined by its appearance and usage in the GP expressions. Features that are frequently used or have a strong influence on the resulting mapping are typically considered important. However, the specific reasons for their importance may vary depending on the dataset and the problem being addressed.



Fig. 10: COIL Case Study Chat

Using the chatbot, we ask "What makes a feature important?". In Fig. 10(a), the LLM informs us important features have a significant impact on the mapping from the highdimensional space to the low-dimensional space. It continues to explain the importance is determined by the feature's appearance and usage in the expressions. Frequently used features or those having a strong influence on the mapping are considered important.

To further explore the importance of features in the dataset, we ask the LLM in Fig. 10(b) to name the ten most significant features. Initially, it assesses the first dimension. f509 appears twice, with one instance high up in the tree, having a significant influence on the outcome. f602 also appears high up in the tree, presents itself 4 times, and is on both sides of the root max node. f423 is featured in the next level, and f583 appears five times, with two instances in the subsequent level. Moving to the second dimension, f56 with 6 occurrences has 2 of these instances high up in the tree on both sides of the root max node. f778 with 4 occurrences sits alongside f56 on the 3rd level of the tree. f1022, f814, f157, and f770 complete the top 10.

To highlight the multilingual capabilities of the chatbot, we ask it in French "*Est-ce une bonne réduction?*" meaning "*Is this a good reduction?*". The chatbot also responds in French, as shown in Fig. 10(c). Using Google Translate, we can translate this back to English, which gives us: "*Reducing* 1024 features to 2 dimensions using GP-MaL-2 is not very good. The precision of the reduced dimensional space is only 0.6375, which is significantly lower than the precision of the original dataset (0.9868). This suggests that reduced features may not capture enough information or discriminate well between different classes or patterns in the COIL20 dataset. It is possible that the mapping expressions used in GP-MaL-2 did not effectively capture the underlying data structure". The multilingual ability of LLMs is a significant opportunity for making advances in AI accessible to a wider audience.

V. DISCUSSION

The experiments in this study confirm the effectiveness of an XAI dashboard in communicating the results of GP-NLDR. Leveraging LLMs such as ChatGPT effectively contributes to user-centred explanations through conversational chatbot technology. Employing AI-powered web-based applications such as GP4NLDR draws on the latest cutting-edge research delivering state-of-the-art tools to individuals. In this section, we discuss several of our findings in more detail. We believe that aspects of this discussion could be very useful in guiding the development of methods integrating GP and LLMs.

Prompt engineering is a dynamic and evolving field requiring careful crafting to steer models towards relevant and accurate responses. Recently, it has gained significant attention due to its pivotal role in shaping the behaviour of LLMs. The trend towards formalising prompt structures has given rise to defining prompt techniques such as zeroshot, few-short, chain-of-thought, tree-of-thought, and more. In this work, we adopt a combination of techniques. Structured prompting can effectively maintain a uniform tone in chatbot responses. However, in our setting, this is not of paramount concern. Our developed prompt, although slightly verbose and unstructured, introduces novelty and diversity, enabling the LLM to craft its responses creatively if desired. Avoiding explicitly requesting a fixed response structure, such as bullet points, sentences, paragraphs, or abbreviations, contributes to enhancing engagement with the chatbot. Furthermore, in targeting a *user-centred* approach, we do not seek to impose restrictions on response style, which may potentially hinder ingenuity and interest when generating explanations. However, potentially allowing the user an option to indicate their level of comprehension may facilitate a more tailored response tone, which could be addressed in future work.

Data privacy concerns within LLM-powered applications continue to be at the forefront of discussions in research and industry. End-users interacting with AI applications should seek reassurance in knowing the confidentiality and security of their data is maintained, especially sensitive and personal information. In this work we demonstrated within the prompt template no raw data is transmitted to the LLM, only the dataset name and feature list. Nonetheless, this does not prevent the user from entering sensitive information and transmitting it voluntarily.

Hallucinations are a growing concern in developing applications integrating LLMs. Throughout the development of this work, we witnessed entirely fictional information returned from the models following questioning. To reduce the incidence of hallucinations, we integrated our tailored prompt template with retrieval augmented generation (RAG). This generally addressed this problem, but, unfortunately, no robust solution has yet been identified to circumvent these situations. Throughout the development of the prompt, we encountered guardrails imparting superfluous advice not pertinent to providing further explanations. Ongoing research in LLMs is expected to address this. We also note other recent concerns arising with the use of LLMs in applications such as adversarial attacks [56] and bias within the models and their benchmarks [57]. It is not within the scope of this work to delve into these issues further, but we acknowledge these challenges are of ongoing concern and necessitate further research.

Rapid advancements are frequently seen in the fast-moving domain of generative AI. During the preparation of this paper, recent announcements such as ChatGPT Enterprise have been regularly released. The edition boasts an extended token limit of 32k (4 times the current capacity), enterprise-grade privacy and security, and the expansion of model knowledge through integration with company data¹⁶. Within our research setting, an increased token limit may enable the complete list of feature names for higher-dimensional datasets to be included in the LLM prompt, eliminating the need for truncation. Occasionally, exceptionally lengthy GP expressions may surpass the current token limit; an extended token limit may be advantageous in some scenarios. With the addition of extra privacy measures, the prompt could be enriched to include a subset of dataset rows. Supplementing the model with this information may enhance the conversational explanations. The facility to integrate company data would be an ideal alternative to using RAG. These innovations will continue to address ongoing concerns in developing AI-driven applications.

Future work could delve deeper into the use of LLMs for explaining GP expressions in other fundamental machine learning tasks. Exploring other retrieval methods and/or alternative vector store approaches has the potential to further improve the efficacy of our framework. In addition, exploring alternative architectures to the Langchain framework used in this study may offer further avenues for harnessing LLMs. Our work touched on the feasibility of leveraging other open-source LLMs. Further development of tailored prompt templates and consideration of fine-tuning these models could be advantageous in assessing their performance comparison with ChatGPT. Exploring the extension of chat parameters, such as explicitly targeting different audiences, may improve user experience and the understanding of explanations. To more rigorously validate our research, future work will include human evaluation of the explanations [58]. Through usergroup experiences we may assess the quality of results on a larger scale and endeavour to provide measurable benchmarks for use in subsequent research within this domain.

VI. CONCLUSION

This study presented a novel dashboard application to explain the results of GP-based nonlinear dimensionality reduc10

tion. Our proposed approach cohesively incorporates a variety of techniques, including a user interface, visualisation, a large language model chatbot, retrieval augmented generation, and prompt engineering to provide a system that greatly improves the explainability of GP. This is the first study of its kind encapsulating these elements within a unified system, spanning the domains of evolutionary computation and generative AI. We presented three robust case studies to highlight the usability of our research in this field. Incorporating a chatbot built on groundbreaking LLM techniques provides significant improvements to the explainability of GP expressions, with potential implications for the wider GP community. Furthermore, we have highlighted how leveraging LLMs for conversation provides a *user-centred* approach accommodating the needs of a diverse audience. Our work has contributed to the gap in research around leveraging generative AI in explainable evolutionary computation.

REFERENCES

- Y. Mei, Q. Chen, A. Lensen, B. Xue, and M. Zhang, "Explainable artificial intelligence by genetic programming: A survey," *IEEE Transactions* on Evolutionary Computation, vol. 27, no. 3, pp. 621–641, 2023.
- [2] T. P. Quinn, S. Jacobs, M. Senadeera, V. Le, and S. Coghlan, "The three ghosts of medical AI: Can the black-box present deliver?" *Artificial Intelligence in Medicine*, vol. 124, p. 102158, 2022.
- [3] Z. Salahuddin, H. C. Woodruff, A. Chatterjee, and P. Lambin, "Transparency of deep neural networks for medical image analysis: A review of interpretability methods," *Computers in Biology and Medicine*, vol. 140, p. 105111, 2022.
- [4] O. Kuiper, M. van den Berg, J. van der Burgt, and S. Leijnen, "Exploring explainable AI in the financial sector: Perspectives of banks and supervisory authorities," in *Artificial Intelligence and Machine Learning*, L. A. Leiva, C. Pruski, R. Markovich, A. Najjar, and C. Schommer, Eds. Cham: Springer International Publishing, 2022, pp. 105–119.
- [5] M. Ribera and A. Lapedriza, "Can we do better explanations? A proposal of user-centered explainable AI," in *Intelligent User Interfaces (IUI) Workshops*, 2019.
- [6] T. Miller, "Explanation in artificial intelligence: Insights from the social sciences," Artificial Intelligence, vol. 267, pp. 1–38, 2019.
- [7] P. Maddigan and T. Susnjak, "Chat2vis: Fine-tuning data visualisations using multilingual natural language text and pre-trained large language models," *arXiv preprint arXiv:2303.14292*, 2023.
- [8] —, "Chat2vis: Generating data visualizations via natural language using chatgpt, codex and gpt-3 large language models," *IEEE Access*, vol. 11, pp. 45 181–45 193, 2023.
- [9] C. Haider, F. O. de Franca, B. Burlacu, F. Bachinger, G. Kronberger, and M. Affenzeller, *Shape-constrained Symbolic Regression: Real-World Applications in Magnetization, Extrusion and Data Validation.* Singapore: Springer Nature Singapore, 2024, pp. 225–240.
- [10] S. Nguyen, D. Thiruvady, Y. Sun, and M. Zhang, "Genetic-based constraint programming for resource constrained job scheduling," *arXiv* preprint arXiv:2402.00459, 2024.
- [11] Q. Fan, Y. Bi, B. Xue, and M. Zhang, "A genetic programming-based method for image classification with small training data," *Knowledge-Based Systems*, vol. 283, p. 111188, 2024.
- [12] Q. U. Ain, B. Xue, H. Al-Sahaf, and M. Zhang, "Skin cancer detection with multimodal data: A feature selection approach using genetic programming," in *Data Science and Machine Learning*, D. Benavides-Prado, S. Erfani, P. Fournier-Viger, Y. L. Boo, and Y. S. Koh, Eds. Singapore: Springer Nature Singapore, 2024, pp. 254–269.
- [13] L. Wu, L. Yuan, G. Zhao, H. Lin, and S. Z. Li, "Deep clustering and visualization for end-to-end high-dimensional data analysis," *IEEE Transactions on Neural Networks and Learning Systems*, pp. 1–12, 2022.
- [14] Q. V. Nguyen, M. Lin Huang, and S. Simoff, "Enhancing scatter-plots with start-plots for visualising multi-dimensional data," in 2020 24th International Conference Information Visualisation (IV), 2020, pp. 80– 85.
- [15] S. J. Fernstad, A. Macquisten, J. Berrington, N. Embleton, and C. Stewart, "Quality Metrics to Guide Visual Analysis of High Dimensional Genomics Data," in *EuroVis Workshop on Visual Analytics (EuroVA)*, C. Turkay and K. Vrotsou, Eds. The Eurographics Association, 2020.

¹⁶https://openai.com/blog/introducing-chatgpt-enterprise

- [16] A. Agrawal and C. McComb, "Comparing strategies for visualizing the high-dimensional exploration behavior of cps design agents," in 2022 *IEEE Workshop on Design Automation for CPS and IoT (DESTION)*, 2022, pp. 64–69.
- [17] A. Lensen, B. Xue, and M. Zhang, "Genetic programming for evolving a front of interpretable models for data visualization," *IEEE Transactions* on Cybernetics, vol. 51, no. 11, pp. 5468–5482, 2021.
- [18] T. Uriot, M. Virgolin, T. Alderliesten, and P. A. N. Bosman, "On genetic programming representations and fitness functions for interpretable dimensionality reduction," in *Proceedings of the Genetic and Evolutionary Computation Conference*. ACM, 2022.
- [19] A. Lensen, B. Xue, and M. Zhang, "Can genetic programming do manifold learning too?" in *Proceedings of the European Conference on Genetic Programming (EuroGP), Lecture Notes in Computer Science.* Springer International Publishing, 2019, vol. 11451, pp. 114–130.
- [20] A. Lensen, M. Zhang, and B. Xue, "Multi-objective genetic programming for manifold learning: balancing quality and dimensionality," *Genetic Programming and Evolvable Machines*, vol. 21, no. 3, pp. 399– 431, feb 2020.
- [21] F. Schofield and A. Lensen, "Using genetic programming to find functional mappings for umap embeddings," in 2021 IEEE Congress on Evolutionary Computation (CEC), 2021, pp. 704–711.
- [22] L. Longo, M. Brcic, F. Cabitza, J. Choi, R. Confalonieri, J. D. Ser, R. Guidotti, Y. Hayashi, F. Herrera, A. Holzinger, R. Jiang, H. Khosravi, F. Lecue, G. Malgieri, A. Páez, W. Samek, J. Schneider, T. Speith, and S. Stumpf, "Explainable artificial intelligence (XAI) 2.0: A manifesto of open challenges and interdisciplinary research directions," *Information Fusion*, vol. 106, p. 102301, 2024.
- [23] S. Ali, T. Abuhmed, S. El-Sappagh, K. Muhammad, J. M. Alonso-Moral, R. Confalonieri, R. Guidotti, J. Del Ser, N. Díaz-Rodríguez, and F. Herrera, "Explainable artificial intelligence (XAI): What we know and what is left to attain trustworthy artificial intelligence," *Information Fusion*, vol. 99, p. 101805, 2023.
- [24] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Proceedings of the 31st International Conference* on Neural Information Processing Systems, ser. NIPS'17. Curran Associates, 2017, p. 4768–4777.
- [25] M. T. Ribeiro, S. Singh, and C. Guestrin, ""Why should i trust you?" explaining the predictions of any classifier," in *Proceedings of the 22nd* ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. Association for Computing Machinery, 2016, pp. 1135– 1144.
- [26] J. Klaise, A. V. Looveren, G. Vacanti, and A. Coca, "Alibi explain: Algorithms for explaining machine learning models," *Journal of Machine Learning Research*, vol. 22, no. 181, pp. 1–7, 2021.
- [27] R. K. Mothilal, A. Sharma, and C. Tan, "Explaining machine learning classifiers through diverse counterfactual explanations," in *Proceedings* of the 2020 Conference on Fairness, Accountability, and Transparency, 2020, pp. 607–617.
- [28] M. Venturini, I. Van Keilegom, W. De Corte, and C. Vens, "Predicting time-to-intubation after critical care admission using machine learning and cured fraction information," *Artificial Intelligence in Medicine*, vol. 150, p. 102817, 2024.
- [29] P. Maddigan and T. Susnjak, "Forecasting patient demand at urgent care clinics using machine learning," arXiv preprint arXiv:2205.13067, 2022.
- [30] I. Hussain and R. Jany, "Interpreting stroke-impaired electromyography patterns through explainable artificial intelligence," *Sensors*, vol. 24, no. 5, 2024.
- [31] F. Afrin, M. Hamilton, and C. Thevathyan, "Exploring counterfactual explanations for predicting student success," in *Computational Science – ICCS 2023*, J. Mikyška, C. de Mulatier, M. Paszynski, V. V. Krzhizhanovskaya, J. J. Dongarra, and P. M. Sloot, Eds. Cham: Springer, 2023, pp. 413–420.
- [32] N. R. Raji, R. M. S. Kumar, and C. L. Biji, "Explainable machine learning prediction for the academic performance of deaf scholars," *IEEE Access*, vol. 12, pp. 23595–23612, 2024.
- [33] M. Kuźba and P. Biecek, "What would you ask the machine learning model? identification of user needs for model explanations based on human-model conversations," in *ECML PKDD 2020 Workshops*. Springer International Publishing, 2020, pp. 447–459.
- [34] M. Guimaraes, J. Baptista, and M. Sousa, "A conversational interface for interacting with machine learning models," 2022.
- [35] V. B. Nguyen, J. Schlötterer, and C. Seifert, "Explaining machine learning models in natural conversations: Towards a conversational XAI agent," *arXiv preprint arXiv:2209.02552*, 2022.

- [36] S. Luke and L. Panait, "A comparison of bloat control methods for genetic programming," *Evolutionary Computation*, vol. 14, no. 3, pp. 309–344, 2006.
- [37] B. Tran, B. Xue, and M. Zhang, "Genetic programming for feature construction and selection in classification on high-dimensional data," *Memetic Computing*, vol. 8, no. 1, pp. 3–15, 2016.
- [38] E. Cambria, L. Malandri, F. Mercorio, M. Mezzanzanica, and N. Nobani, "A survey on XAI and natural language explanations," *Information Processing & Management*, vol. 60, no. 1, p. 103111, 2023.
- [39] C. Singh, J. P. Inala, M. Galley, R. Caruana, and J. Gao, "Rethinking interpretability in the era of large language models," *arXiv preprint* arXiv:2402.01761, 2024.
- [40] C. C. Sartori, C. Blum, and G. Ochoa, "Large language models for the automated analysis of optimization algorithms," *arXiv preprint* arXiv:2402.08472, 2024.
- [41] C. Chacón Sartori, C. Blum, and G. Ochoa, "Stnweb: A new visualization tool for analyzing optimization algorithms," *Software Impacts*, vol. 17, p. 100558, 2023.
- [42] Y. Lappalainen and N. Narayanan, "Aisha: A custom AI library chatbot using the ChatGPT API," *Journal of Web Librarianship*, vol. 17, no. 3, pp. 37–58, 2023.
- [43] A. Rau, S. Rau, D. Zöller, A. Fink, H. Tran, C. Wilpert, J. Nattenmüller, J. Neubauer, F. Bamberg, M. Reisert, and M. F. Russe, "A context-based chatbot surpasses radiologists and generic ChatGPT in following the ACR appropriateness guidelines," *Radiology*, vol. 308, no. 1, p. e230970, 2023.
- [44] M. Zaib, W. E. Zhang, Q. Z. Sheng, A. Mahmood, and Y. Zhang, "Conversational question answering: a survey," *Knowledge and Information Systems*, vol. 64, pp. 3151–3195, 2022.
- [45] H. Chase, "LangChain," Oct. 2022. [Online]. Available: https: //github.com/hwchase17/langchain
- [46] S. Luke and L. Panait, "Lexicographic parsimony pressure," in Proceedings of the 4th Annual Conference on Genetic and Evolutionary Computation, 2002, pp. 829–836.
- [47] —, "Fighting bloat with nonparametric parsimony pressure," in *Parallel Problem Solving from Nature PPSN VII*. Springer, 2002, pp. 411–421.
- [48] R. Poli, "A simple but theoretically-motivated method to control bloat in genetic programming," in *Genetic Programming*. Springer, 2003, pp. 204–217.
- [49] L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
- [50] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
- [51] P. Lewis, E. Perez, A. Piktus, F. Petroni, V. Karpukhin, N. Goyal, H. Küttler, M. Lewis, W.-t. Yih, T. Rocktäschel, S. Riedel, and D. Kiela, "Retrieval-augmented generation for knowledge-intensive nlp tasks," in *Advances in Neural Information Processing Systems*, H. Larochelle, M. Ranzato, R. Hadsell, M. Balcan, and H. Lin, Eds., vol. 33. Curran Associates, Inc., 2020, pp. 9459–9474.
- [52] J. Johnson, M. Douze, and H. Jégou, "Billion-scale similarity search with GPUs," *IEEE Transactions on Big Data*, vol. 7, no. 3, pp. 535– 547, 2019.
- [53] S. Aeberhard and M. Forina, "Wine," UCI Machine Learning Repository, 1991.
- [54] N. Ilter and H. Guvenir, "Dermatology," UCI Machine Learning Repository, 1998.
- [55] S. A. Nene, S. K. Nayar, and H. Murase, "Columbia object image library (coil-20)," Department of Computer Science, Columbia University, Tech. Rep. CUCS-005-96, February 1996. [Online]. Available: https://www. bibsonomy.org/bibtex/2e21afb22e024792723fc3b9f659c522e/jabreftest
- [56] A. Zhou, B. Li, and H. Wang, "Robust prompt optimization for defending language models against jailbreaking attacks," arXiv preprint arXiv:2401.17263, 2024.
- [57] T. R. McIntosh, T. Susnjak, T. Liu, P. Watters, and M. N. Halgamuge, "Inadequacies of large language model benchmarks in the era of generative artificial intelligence," arXiv preprint arXiv:2402.09880, 2024.
- [58] C. van der Lee, A. Gatt, E. van Miltenburg, S. Wubben, and E. Krahmer, "Best practices for the human evaluation of automatically generated text," in *Proceedings of the 12th International Conference on Natural Language Generation*, K. van Deemter, C. Lin, and H. Takamura, Eds. Tokyo, Japan: Association for Computational Linguistics, 2019, pp. 355– 368.

Appendix



Fig. 11: Wine Case Study Results from GP4NLDR

The GP-MaL algorithm successfully reduced the original 13 features of the Wine dataset to 2 new dimensions. In the first dimension, the feature expression includes the Flavanoids (f6) feature, which suggests that this feature is important in distinguishing between different wine samples. In the second dimension, the expression includes the Proline (f12), Color intensity (f9), and Alcohol (f0) features, indicating their significance in the dataset. The other features are less important in the context of the dataset, as they are not included in the GP expressions.

explain the 2nd dimension further

In the second dimension, the expression includes the Proline (f12), Color intensity (f9), and Alcohol (f0) features. This suggests that these features play a crucial role in determining the characteristics of the wine samples in the dataset. Proline is an amino acid found in grapes and is known to contribute to the flavor and quality of wines. Color intensity is an important factor in wine evaluation, as it provides information about the concentration of pigments in the wine. Alcohol content is also a significant feature in wine analysis, as it affects the taste, aroma, and overall quality of the wine. Therefore, these features are considered important in the context of the dataset.

more info about the first dimension please

In the first dimension, the expression includes the Flavanoids (f6) feature. Flavanoids are a class of compounds found in grapes and are known to contribute to the color, flavor, and antioxidant properties of wines. The inclusion of this feature in the expression suggests that it plays a significant role in distinguishing between different wine samples based on their characteristics. Therefore, the Flavanoids feature is considered important in the context of the dataset.

what is gpmal?

GP-MaL stands for Genetic Programming for Manifold Learning. It is an algorithm that uses genetic programming to evolve functional mappings from a high-dimensional space to a lower-dimensional space. The goal of GP-MaL is to find interpretable trees that can effectively reduce the dimensionality of a dataset while preserving important information. GP-MaL-2 is a variant of GP-MaL and is the first objective of GP-MaL-MO, which is a multi-objective approach that balances manifold quality and dimensionality.

was this a good reduction in dimensions?

Yes, the reduction in dimensions achieved by GP-MaL was effective. The original dataset had 13 features, and GP-MaL successfully reduced it to 2 new dimensions. The accuracy of the new dimensional space is 0.9333, which indicates that the reduced dimensions still capture a significant amount of information from the original dataset. While there is a slight decrease in accuracy compared to the original dataset (0.9833), the reduction in dimensions allows for easier visualization and potentially simplifies the analysis of the dataset.

what is hue?

"Hue" (f10) refers to the attribute of color in the wine samples. It represents the perceived color tone of the wine, ranging from red to yellow. The hue of a wine can provide information about its age, grape variety, and winemaking techniques. However, in the context of the GP expressions and the reduced dimensions, the "Hue" feature was not deemed as important for distinguishing between different wine samples.



Fig. 13: Dermatology Case Study Results from GP4NLDR

The results of the GP expressions from NLDR show that the original 34 features of the Dermatology dataset have been reduced to new features in 3 dimensions. In Dimension 0, the important features are knee and elbow involvement, munro microabcess, elongation of the rete ridges, clubbing of the rete ridges, and family history. These features are likely important in distinguishing different types of skin conditions. In Dimension 1, the important features are clubbing of the rete ridges, perifollicular parakeratosis, spongiosis, spongiform pustule, and the absolute subtract of definite borders and family history. These features are disappearance of the granular layer, definite borders, vacuolisation and damage of basal layer, a constant value, and melanin incontinence. These features might be indicative of certain skin conditions or abnormalities. Overall, the accuracy of the new dimensional space is slightly lower than the original dataset, suggesting that some information may have been lost during the dimensionality reduction process.

How could this dimensionality reduction be improved?

To improve the dimensionality reduction, several approaches can be considered. First, different GP operators or combinations of operators can be explored to generate more effective expressions. Additionally, the population size and number of generations can be adjusted to allow for more thorough exploration of the solution space. Furthermore, alternative fitness measures or bloat control methods can be employed to encourage the evolution of more compact and accurate expressions. Finally, incorporating domain knowledge or expert guidance into the GP process can help guide the search towards more meaningful and informative feature expressions.

is gpmal better than gpmal2?

Based on the provided information, it is not possible to determine whether GP-MaL is better than GP-MaL-2. The prompt only mentions that GP-MaL-2 is the first objective of GP-MaL-MO, but it does not provide any specific details or comparisons between the two approaches. Further information or analysis would be needed to make a comparison between GP-MaL and GP-MaL-2.

how does erythema fit in here?

In the given GP expressions for NLDR, the feature "erythema" (f0) is not explicitly mentioned as an important feature in any of the three dimensions. This suggests that erythema may have less influence or relevance in distinguishing the different types of skin conditions represented in the Dermatology dataset. However, it is important to note that the absence of erythema in the GP expressions does not necessarily mean it is irrelevant overall. Other features may capture similar information or erythema may still contribute to the overall accuracy of the original dataset.

what if i am really old and itchy?

Based on the provided GP expressions for NLDR, neither the feature "age" (f33) nor the feature "itching" (f3) are explicitly mentioned as important features in any of the three dimensions. This suggests that the combination of being really old and itchy may have less influence or relevance in determining the type of skin condition represented in the Dermatology dataset. However, it is important to note that the absence of these features in the GP expressions does not necessarily mean they are irrelevant overall. Other features may capture similar information or age and itching may still contribute to the overall accuracy of the original dataset.

Fig. 14: Dermatology Case Study Chat Conversation Examples



Fig. 15: COIL20 Case Study Results from GP4NLDR

The GP-MaL-2 algorithm was used to reduce the dimensionality of the COIL20 dataset from 1024 features to 2 dimensions. The accuracy of the original dataset was 0.9868, while the accuracy of the reduced dimensional space was 0.6375. In the first dimension, features such as f509, f602, f423, and f583 were important, while features like f157, f770, and f514 were less important. In the second dimension, features like f56, f778, f1022, and f814 were important, while features like f289, f195, and f68 were less important. The importance of these features in the context of the dataset is not explicitly mentioned in the given information.

Could I correctly classify an image from using the new dimensional space?

Based on the given information, it is not possible to determine if the new dimensional space obtained through the dimensionality reduction using GP-MaL-2 can be used for accurate image classification. The accuracy of the reduced dimensional space is 0.6375, which is significantly lower than the accuracy of the original dataset (0.9868). This suggests that the reduced dimensional space may not capture all the necessary information for accurate image classification. Further analysis and evaluation would be needed to determine if the reduced dimensional space can be effectively used for image classification tasks

What are the 10 most important features?

The 10 most important features in the GP expressions for the reduced dimensional space are f509, f602, f423, f583, f56, f778, f1022, f814, f157, and f770.

What makes a feature important?

In the context of dimensionality reduction using GP, a feature is considered important if it has a significant impact on the mapping from the high-dimensional space to the lower dimensional space. This can be determined by its appearance and usage in the GP expressions. Features that are frequently used or have a strong influence on the resulting mapping are typically considered important. However, the specific reasons for their importance may vary depending on the dataset and the problem being addressed.

Est-ce une bonne réduction ?

La réduction de 1024 caractéristiques à 2 dimensions en utilisant GP-MaL-2 n'est pas très bonne. La précision de l'espace dimensionnel réduit est seulement de 0,6375, ce qui est nettement inférieur à la précision de l'ensemble de données d'origine (0,9868). Cela suggère que les caractéristiques réduites peuvent ne pas capturer suffisamment d'informations ou ne pas bien discriminer entre différentes classes ou motifs dans l'ensemble de données COIL20. Il est possible que les expressions de mappage utilisées dans GP-MaL-2 n'aient pas efficacement capturé la structure sous-jacente des données.

Fig. 16: COIL20 Case Study Chat Conversation Examples