## VERBALIZED GRAPH REPRESENTATION LEARNING: A FULLY INTERPRETABLE GRAPH MODEL BASED ON LARGE LANGUAGE MODELS THROUGHOUT THE ENTIRE PROCESS

Anonymous authors

Paper under double-blind review

#### ABSTRACT

Representation learning on text-attributed graphs (TAGs) has attracted significant interest due to its wide-ranging real-world applications, particularly through Graph Neural Networks (GNNs). Traditional GNN methods focus on encoding the structural information of graphs, often using shallow text embeddings for node or edge attributes. This limits the model to understand the rich semantic information in the data and its reasoning ability for complex downstream tasks, while also lacking interpretability. With the rise of large language models (LLMs), an increasing number of studies are combining them with GNNs for graph representation learning and downstream tasks. While these approaches effectively leverage the rich semantic information in TAGs datasets, their main drawback is that they are only partially interpretable, which limits their application in critical fields. In this paper, we propose a verbalized graph representation learning (VGRL) method which is fully interpretable. In contrast to traditional graph machine learning models, which are usually optimized within a continuous parameter space, VGRL constrains this parameter space to be text description which ensures complete interpretability throughout the entire process, making it easier for users to understand and trust the decisions of the model. We conduct several studies to empirically evaluate the effectiveness of VGRL and we believe this method can serve as a stepping stone in graph representation learning. The source code of our model is available at https://anonymous.4open.science/r/VGRL-7E1E

000

001

002

004

006

008

009

010 011 012

013

015

016

017

018

019

021

024

025

026

027

028

029

031

#### 1 INTRODUCTION

Many real-world graphs incorporate textual data, forming what are known as Text-Attributed Graphs 037 (TAGs) (Yang et al., 2021). In TAGs, nodes represent textual entitities such as papers, while edges denote relationships between them, such as citations or co-authorships. For instance, the Cora dataset can be modeled as a TAG, where each node represents a research paper, and the node at-040 tributes include features such as the paper's title, abstract, and keywords. By integrating textual 041 attributes with graph topology, TAGs facilitate more effective representation learning, making them 042 valuable for tasks like document classification, clustering (Wang et al., 2023), citation analysis, and 043 recommendation systems (Zhu et al., 2021; Zhang et al., 2023a). This combination of textual and 044 relational data offers deeper insights, especially when both content and connections are essential to 045 the analysis.

Although traditional Graph Neural Network (GNN) models, such as Graph Convolutional Network (GCN) (Kipf & Welling, 2016) and Graph Attention Network (GAT) (Veličković et al., 2017), have achieved significant performance improvements across multiple tasks, they generally suffer from a lack of interpretability. As these models largely rely on complex network architectures and implicit feature learning processes, understanding their internal decision mechanisms and how specific features influence task outcomes becomes challenging, thereby limiting their transparency and trustworthiness in practical applications. To address this issue, researchers have proposed several interpretable GNN models. These interpretable methods can generally be divided into input interpretability, training process interpretability, and decision-making process interpretability. For



Figure 1: Comparison of Graph Representation Learning Methods (a) Traditional Graph Neural Networks (GNNs) rely on graph structures and initial features for embedding generation and prediction. (b) Incorporating a Language Model (LLM) enhances GNNs, where a Large Language Model (LLM) provides explanations that refine the embedding process for improved predictions. (c) Our proposed Verbalized Graph Representation Learning (VGRL) framework introduces an iterative optimization process involving multiple frozen LLMs (Enhancer, Predictor, Optimizer, and Summary), emphasizing interpretability and parameter tuning through verbalized model adjustments.

066

067

068

069

074 example, GNNExplainer (Ying et al., 2019) is a method for input interpretability, which selects a small subgraph of the input graph together with a small subset of node features that are most in-075 fluential for the prediction as an explanation, XGNN (Yuan et al., 2020) is a method for training 076 process interpretability which reveals the basis of the model's predictions by generating interpretable 077 graph structures, and SE-SG former (Li et al., 2024a) is a method for decision-making process interpretability which constructs a novel explainable decision process by discovering the K-nearest 079 (farthest) positive (negative) neighbors of a node for predicting edge signs. Clearly, while these methods all have a certain degree of interpretability, they can only explain one part of the entire 081 process of model input, training, and output. Therefore, our goal is to implement comprehensive 082 interpretability by simultaneously achieving input interpretability, training process interpretability, 083 and decision-making process interpretability.

- 084 In recent years, with the breakthroughs of large language models (LLMs) in the field of natural 085 language processing, researchers have gradually begun to integrate them with GNNs to enhance model performance and capabilities. For instance, LLMs can act as predictors (Tang et al., 2024), 087 generating more accurate predictions by analyzing node features and structural information for the 880 TAGs. Also, TAPE (He et al., 2023) prompts a powerful LLM to explain its predictions and serve explanations as supplementary text attributes for the downstream LMs and GNN models. Due to 090 the powerful text inference capabilities of LLMs, they are capable of processing TAGs, reasoning 091 about the node classification prediction process of TAGs, and generating explanations in text that is comprehensible to humans. Therefore, we consider the use of LLMs to achieve comprehensive 092 interpretability. However, using LLMs to handle graph tasks and provide interpretability is not easy. 093 Specifically, there are currently two main approaches to applying LLMs in the field of graph: one 094 is to pre-train or fine-tune LLMs to adapt to various graph downstream tasks. But due to the vast 095 number of parameters typically found in LLMs, the cost of fine-tuning LLMs is quite high and the 096 training time is long. The second is to directly freeze the LLMs for inference but this method does not yield good results. For example, we directly froze the predictor LLMs for node classification 098 prediction in subsequent experiments, and the prediction accuracy was generally not high, as shown 099 in Table 3. 100
- In summary, we face two major challenges to achieve comprehensive interpretability with LLMs:
- 102 Challenge 1: How can we ensure that a model is interpretable in terms of input, training process, and decision-making simultaneously?
- Challenge 2: How can we optimize the performance of LLMs without fine-tuning the model parameters to reduce costs?
- 107 To address these challenges, we propose the Verbalized Graph Representation Learning (VGRL) method. For Challenge 1, VGRL utilizes a verbalized approach to create intuitive connections

108 between input features and predictions and VGRL generates textual explanations at each iteration 109 stage, helping researchers and practitioners better grasp the training dynamics of the model. Also, 110 VGRL provides natural language descriptions for the model's predictions, clearly explaining the ra-111 tionale behind each decision. For Challenge 2, instead of relying on costly fine-tuning of the LLM 112 parameters, VGRL leverages a prompt-based optimization strategy. This involves crafting taskspecific prompts to guide the LLM in generating optimal predictions without modifying its internal 113 parameters. By utilizing prompt engineering techniques, VGRL maintains high performance while 114 significantly reducing computational costs associated with traditional fine-tuning methods. Addi-115 tionally, this approach allows the model to remain versatile across various tasks, as it can be adapted 116 to new datasets or problems simply by adjusting the prompts, further enhancing its efficiency and 117 scalability. 118

119 Our contributions are as follows:

- We propose a novel verbalized graph learning framework that ensures complete interpretability throughout the entire process, from input to training and decision-making, enabling users to fully understand the operational mechanisms of the model.
  - We seek to reduce the high GPU overhead associated with pre-training or fine-tuning in current graph plus LLMs paradigms by utilizing a new model optimization approach, known as Iterative Training through Prompt Optimization.
  - We validate the effectiveness of this method from multiple perspectives on real-world datasets.
- 130 🤈 Dī
- 131

120

121

122

123

124

125

126 127

128 129

2 PRELIMINARIES

In this section, we introduce the essential concepts, notations, and problem settings considered in
 this research. Our primary focus is on the node classification task over text-attributed graphs, which
 represents a fundamental downstream task within the field of graph learning. We begin by defining
 text-attributed graphs.

**Text-Attributed Graphs.** Text-attributed graphs (TAGs) can be formally described as  $\mathcal{G} = (\mathcal{V}, \mathcal{A}, \{\mathcal{X}_n\}_{n \in \mathcal{V}})$ , where  $\mathcal{V}$  represents a set of  $\mathcal{N}$  nodes,  $\mathcal{A} \in \mathbb{R}^{\mathcal{N} \times \mathcal{N}}$  is the adjacency matrix, and  $\mathcal{X}_n \in \mathcal{D}^{\mathcal{L}_n}$  denotes a sequential text associated with each node  $v_n \in \mathcal{V}$ . Here,  $\mathcal{D}$  is the dictionary of words or tokens, and  $\mathcal{L}_n$  is the length of the sequence. In this paper, we focus on the problem of node classification in TAGs. Specifically, given a subset of labeled nodes  $\mathcal{L} \subseteq \mathcal{V}$ , the task is to predict the labels of the remaining unlabeled nodes  $\mathcal{U} = \mathcal{V} \setminus \mathcal{L}$ . And iterates over the input mini-batch  $\mathcal{B}$  one-pass input.

143 144 145 **One-hop neighbors.** Given a node  $v_i \in \mathcal{V}$ , the set of one-hop neighbors, denoted as  $\mathcal{N}(v)$ , where  $\mathcal{N}(v_i) = \{v_j \in \mathcal{V} | (v_i, v_j) \in \mathcal{E}\}$ 

146 *k*-hop neighbors. Given a node  $v_i$ , for  $k \ge 2$ , the *k*-hop neighbors of  $v_i$  can be denoted as  $\mathcal{N}^k(v_i)$ , 147 where  $\mathcal{N}^k(v_i) = \{v_j \in \mathcal{V} \mid \exists v_m \in \mathcal{N}^{k-1}(v_i), (v_m, v_j) \in \mathcal{E} \land v_j \notin \mathcal{N}^{k-1}(v_i)\}.$ 

148 149

#### **3** Related Work

150 151

In this section, we review the existing literature related to integrating Large Language Models (LLMs) and Graph Neural Networks (GNNs). Prior work has focused on several key areas, including traditional methods for trusted GNNs, the role of LLMs in graph-based tasks, and recent advances in optimization frameworks utilizing LLMs. We explore these approaches to highlight their contributions and limitations, establishing the foundation for our proposed Verbalized Graph Representation Learning (VGRL) framework.

- 157 158
- 158 3.1 GRAPH AND LLMS159

Traditional approaches to trusted GNNs. There are currently two main approaches: post-hoc
 explanation methods and self-interpretable models. The former tries to interpret the output of the model by adding a model-independent interpreter, for example (Ying et al., 2019; Vu & Thai, 2020;

Zhang et al., 2023b). However, this can lead to incomplete explanatory information in the output, or
even generate explanatory information that is incorrect in the opinion of humans. The latter tries to
solve this problem by constructing models that themselves have interpretable principles, for example
(Dai & Wang, 2021; Zhang et al., 2022a). However, these interpretable principles are based on their
inductive bias, and only experts in the relevant fields can accurately judge whether such inductive
bias is reasonable or not.

168 LLM in Graph. Existing methods are mainly categorized into three types: (1) LLM as Enhancer 169 which mainly enhances the performance of GNNs by adding LLM-generated information, for ex-170 ample (He et al., 2023; Chen et al., 2024; Ni et al., 2024); (2) LLM as Predictor which mainly 171 performs a downstream task by directly inputting the graph structure into the LLM, for example 172 (Tang et al., 2024; Qin et al., 2023); (3) LLM as Alignment which mainly enhances the performance by aligning embedding spaces of GNNs and LLMs, for example (Yang et al., 2021; Mavromatis 173 et al., 2023). Among them, there is explanation-based LLM-as-Enhancer approach (He et al., 2023), 174 which achieves better performance by letting LLM generate natural language explanation informa-175 tion of graph structures and then embedding it into GNNs for downstream tasks. However, after the 176 embedding from natural language to graph structure is not directly visible as a black box to humans, 177 and can only be proven effective indirectly through the performance of downstream tasks. 178

- 179
- 180
- 181 182

#### 3.2 LLMs Optimization

183

LLMs for planning and optimization. Large language models (LLMs) have been successfully 185 applied to planning tasks for embodied agents (Song et al., 2023; Xie et al., 2023; Li et al., 2022; Liang et al., 2023), enabling them to follow natural language instructions and complete complex 187 tasks. More recently, LLMs have also been utilized to tackle optimization problems by generating 188 new solutions from prompts that incorporate previously generated solutions and their associated loss 189 values. While these LLM-based optimization (Xiao et al., 2024; Yang et al., 2024) methods bear 190 some resemblance to our approach, as we also use LLMs to address optimization challenges, a key 191 limitation of existing work is that it has not yet been explored in the graph domain. To address 192 this gap, we propose an extension of this framework to the graph domain, introducing Verbalized 193 Graph Representation Learning (VGRL), which applies LLMs to graph neural networks (GNNs) 194 and opens new possibilities for solving graph-based optimization problems through natural language interactions. 195

196 Prompt engineering and optimization. Numerous prompting techniques (Wei et al., 2022; Zhang 197 et al., 2022b; Zhou et al., 2022; Wang et al., 2022; Yao et al., 2024; 2023; Weston & Sukhbaatar, 198 2023) have been developed to enhance the reasoning capabilities of LLMs. To minimize the manual 199 effort required in designing effective prompts, various automatic prompt optimization approaches 200 (Zhang et al., 2022b; Zhou et al., 2022; Yang et al., 2024; Pryzant et al., 2023; Wen et al., 2024; 201 Deng et al., 2022; Li et al., 2024b; Ma et al., 2024; Sordoni et al., 2023) have been introduced. However, traditional prompt optimization methods primarily focus on refining the text prompt with-202 out changing its underlying semantic meaning. In contrast, our VGRL framework goes beyond mere 203 prompt adjustments by directly updating the parameters of the language-based model through the 204 integration or modification of prior information. This not only improves optimization but also en-205 sures that the learner model remains fully interpretable in its predictions, offering a more robust and 206 transparent solution for graph-based learning tasks. 207

LLMs for multi-agent systems. Given their strong instruction-following capabilities, LLMs can assume various roles within multi-agent systems (Qian et al., 2023; Wu et al., 2023; Hong et al., 2023; Li et al., 2023). For instance, explore multi-agent collaboration systems designed to solve complex tasks such as software development. In the VGRL framework, this concept is extended to a two-agent system, where one LLM functions as the learner and the other as the optimizer.

Our approach sidesteps the problem of modeling black boxes by having the LLM generate human readable information as promt of another LLM making it perform the downstream task. This can be
 viewed as a "guidance-feedback-redirection" process between models, which, after many iterations, returns the optimal guidance solution for a given task, which is directly human-readable.



Figure 2: An overview of iterative optimization and text prompt templates for the predictor, optimizer, and summary LLM in the node classification example

#### 4 PROPOSED METHOD

In this paper, we present the Verbalized Graph Representation Learning (VGRL) framework, a pioneering approach that integrates large language models (LLMs) with graph-based tasks while ensuring full interpretability throughout the process. Our methodology encompasses four innovative components, each designed to enhance both the performance and the transparency of LLMs in handling graph data.

240 241 242

243

231

232 233 234

235 236

237

238

239

#### 4.1 INCORPORATING GRAPH STRUCTURE INTO LLM PREDICTIONS

Although Large Language Models (LLMs) can achieve competitive zero-shot performance on specific datasets without considering graph structures, their performance often lags behind Graph Neural Networks (GNNs) on benchmark datasets such as CORA, CITESEER, and OGBN-ARXIV. This gap underscores the importance of graph structural information in tasks like node classification, indicating the need to explore how incorporating graph structures into prompts could enhance LLM performance.

Given that LLMs (e.g., ChatGPT) are not natively designed to process adjacency matrices or perform
 graph-based computations, it is impractical to directly integrate graph operations into LLMs. Thus,
 an alternative approach is to verbalize graph information as text that LLMs can process effectively.
 This transformation allows LLMs to interpret node relationships and structural dependencies in
 natural language format. In (Chen et al., 2024), various methods are evaluated to represent node
 connections textually, aiming to enhance LLM reasoning capabilities for graph-based tasks.

One effective method is the 'ego-graph' approach, which focuses on the local subgraph surrounding a target node. By constraining the LLM's focus to a limited number of nodes, this method reduces complexity while preserving key local graph structure. To simulate the neighborhood aggregation process typical in GNNs, the input prompt incorporates a summary of attributes from neighboring nodes. Thus, important information from the graph is conveyed to the LLM without altering its reasoning mechanisms. This process can be formalized as:

261 262 263

$$Z_{v_i}^1 = f_e\left(\mathcal{X}_{v_i}, \left\{\mathcal{X}_{v_j} \mid v_j \in \mathcal{N}(v_i)\right\}\right) \tag{1}$$

where  $Z_{v_i}^1$  is the enhanced representation of node  $v_i$  with one-hop neighbor information,  $\mathcal{X}_{v_i}$  represents the features of node  $v_i$ , and  $\mathcal{N}(v_i)$  denotes the set of one-hop neighbors of  $v_i$ . The function  $f_e$  encapsulates the process of verbalizing neighborhood information and processing it by the LLM.

Inspired by this ego-graph approach, we have also introduced a method for incorporating structural
 information into our model. By embedding the attributes and relationships of neighboring nodes
 into the prompt, we aim to enable the LLM to better capture the interactions between nodes. Below
 is an example of a neighbor summary in Table 1:

	Table 1: Prompts used to generate neighbor summary.
<b>Pron</b> I will the a the c	<b>npts used to summarize the neighboring information</b> now give you basic information about all the papers cited in a paper; this information includes: bstracts and categories of the cited papers. The following list records some papers related to urrent one.
[{ "c	ontent": "This paper firstly provides", "category": "Rule Learning" },]
# Ins Pleas can r Note Pleas	Attraction we summarize the information above with a short paragraph, find some common points which effect the category of this paper. A ONLY your summary information and NOTHING ELSE! We start with "The papers cited in this essay".
4.2	VERBALIZING MODEL PARAMETERS FOR INTERPRETABILITY
Tradi $\theta =$ sente the in (VGI natur	itional machine learning models, such as neural networks, rely on numerical parameters, $\{\theta_1, \theta_2, \ldots, \theta_t\}$ , which are often difficult to interpret. These parameters are typically repred as abstract numerical values, making it complex and non-intuitive to understand or explain internal workings of the model. In contrast, the Verbalized Graph Representation Learning RL) framework leverages large language models (LLMs) to express model parameters through al language, providing full interpretability.
In V natur This hard natur	GRL, the model parameters $\theta_t$ are defined by a text prompt, which consists of human-readable al language tokens, $\theta_t \in \Theta_{\text{language}}$ , where $\Theta_{\text{language}}$ is the set of all interpretable text sequences. approach contrasts with traditional models where parameters are abstract numbers, which are to interpret directly. The VGRL framework unifies both data and model parameters into a al language-based format that is inherently understandable.
The l	key features of this framework include:
	• <b>Discrete Parameters</b> : The natural language used to express parameters $\theta$ is inherently discrete. This is in contrast to the continuous parameter representations in traditional models, enhancing the intuitiveness of parameter interpretation.
	• Sequential Structure: The parameters exhibit a sequential structure, as $\theta = \{\theta_1, \theta_2, \dots, \theta_t\}$ , reflecting the temporal or contextual relationships between parameters. This sequential nature aids in capturing and understanding the dynamics between parameters.
	• Human Interpretability: Since the parameters $\theta_t$ are verbalized in natural language, they are inherently comprehensible to humans. This allows the model's reasoning process and learning mechanisms to be more transparent, facilitating interpretability and easier analysis.
An a prior $\theta_t$ , th examunde	dvantage of using natural language for model parameters is that it enables the integration of knowledge and inductive biases directly into the model. As the model updates its parameters is changes are fully interpretable, providing clear insights into what the model is learning. For pple, changes in $\theta_t$ can be directly mapped to natural language descriptions, offering an intuitive rstanding of the model's learning process.
Our of patter This prove scena	empirical evidence demonstrates that text-based parameters often correspond to recognizable rns in the data, further reinforcing the interpretability and transparency of the VGRL approach. natural language parameterization not only enhances the intuitiveness of model but also im- es its application, offering clearer insights into model tuning and interpretation in real-world arros.
4.3	LEVERAGING LLMS FOR NODE CLASSIFICATION

323 Our approach centers on utilizing LLMs as interpretable predictors by querying them in an 'openended' manner. Unlike existing methods that primarily rely on message passing mechanisms, our method employs a label feature matching mechanism. We match based on the inherent characteris tics of the nodes themselves and the information from their neighbors. This label feature matching
 mechanism places a stronger emphasis on the intrinsic attributes of node, as it aligns with the insights
 provided in the prompt.

The core of this method is represented by the following equation:

- 330
- 331 332

$$\hat{y}_{v_i} = f_p(Z_{v_i}^k, \theta_{t-1})$$
(2)

Here,  $\hat{y}_{v_i}$  denotes the predicted label for node  $v_i$ , and  $Z_{v_i}^k$  represents the enhanced node representation incorporating  $v_i$ 's k-hop neighbors.  $\theta_{t-1}$  refers to the LLM's parameters at the previous step, enabling the model to leverage its prior knowledge and reasoning capabilities to generate the prediction. The function  $f_p$  serves as the predictor that utilizes the enhanced representation and model parameters to produce the label output. This formulation emphasizes the LLM's role as a predictor, focusing on generating interpretable outputs.

For each node  $v_i \in \mathcal{V}$ , a prompt is crafted that includes not only the node's features, such as the paper title and abstract, but also relevant graph structure information. Specifically, the attributes of neighboring nodes up to the *k*-hop neighborhood are embedded in the prompt, as encapsulated in  $Z_{v_i}^k$ . This enables the LLM to better understand the node's context and surroundings within the graph, leading to more informed and accurate predictions.

344 345

4.4 LLM AS AN OPTIMIZER WITH INTERPRETABLE OPTIMIZATION PROCESS

For the predictor LLM, we provide textual descriptions of node categories, which serve as model parameter  $\theta$ , and the model determines which category the input node  $v_i$  belongs to based on the given descriptions. The quality of node category descriptions  $\theta$  directly affects the performance of LLM predictions; hence, obtaining suitable node category descriptions is very important. Additionally, for better explainability, VGRL imposes a strong constraint on  $\theta$ , ensuring that the updated  $\theta$ still belong to natural language sequences that humans can understand.

<sup>352</sup> Under these conditions, it is not advisable to use classical machine learning optimization methods <sup>353</sup> such as gradient descent to optimize  $\theta$ . Inspired by Xiao et al. (2024), the optimizer LLM can output <sup>354</sup> natural language that satisfies the constraints, so we only need to ask the LLM to play the role <sup>355</sup> of an optimizer, then optimized category descriptions are also in natural language understandable <sup>356</sup> by humans. Therefore, we directly use another LLM to optimize  $\theta$ . Given a mini-batch  $\mathcal{B}$ , the <sup>357</sup> optimization process is as follows:

359 360

372

$$P_{v_i}^t = g_{opt}(Z_{v_i}^k, y_{v_i}, \hat{y}_{v_i}, \theta_{t-1}, \Psi), v_i \in \mathcal{B}$$
(3)

where  $y_{v_i}$  is the true label of  $v_i$ ,  $\tilde{\theta}_{v_i}^t$  represents the intermediate parameter values for node  $v_i$  during 361 the t-th iteration, and  $\Psi$  denotes the parameter of the optimizer LLM, which is a text prompt. Specif-362 ically, we optimize the intermediate parameter value  $\hat{\theta}_{v_i}^t$  of each node  $v_i$  in  $\mathcal{B}$ , and then summarize 363 the intermediate parameter values of these nodes through a summary LLM (Section 4.5) to obtain a 364 new round of parameter  $\theta_t$ . The overall framework for optimizer optimization and the text prompt 365 template are given in Figure 2. The parameter  $\Psi$  of the optimizer LLM is actually a text prompt 366 provided by humans and is not updated. The text prompt linguistically specifies the optimization 367 loss function, guiding the optimizer LLM to optimize  $\theta$ . The LLM-parameterized optimizer allows 368 users to interact with it directly, which not only helps to trace model failures but also permits the 369 incorporation of prior knowledge to enhance optimization. In addition, we also guide the LLM 370 to output explanations of the optimization process, demonstrating the explainability of the VGRL 371 optimization process.

373 4.5 SUMMARY LLM374

The role of the Summary LLM is to aggregate and summarize the updated intermediate parameters from the optimizer LLM, generated during the previous minibatch, to obtain updated  $\theta$ . Specifically, given a set of updated parameters from the last minibatch  $\mathcal{B}$ , the Summary LLM consolidates these updates into a new set of parameters,  $\theta_t$ . This process can be formalized as:

382

383

384

385

386 387

388

 $\theta_t = f_s\left(\{\widetilde{\theta}_{v_i}^t \mid v_i \in \mathcal{B}\}\right) \tag{4}$ 

Here,  $\tilde{\theta}_{v_i}^t$  represents the intermediate parameter values for node  $v_i$  during the *t*-th iteration, and  $\mathcal{B}$  denotes the set of nodes in the current minibatch. The function  $f_s$  operates by combining these parameter updates to produce a cohesive set of parameters,  $\theta_t$ , which reflects the overall learning progress across the minibatch. This aggregation ensures that key information from each node's updated parameters is captured while maintaining coherence in the overall optimization process.

#### 4.6 CHAIN-OF-THOUGHT PROMPTING

389 Inspired by (Wei et al., 2022), we introduce the zero-shot and one-shot Chain-of-Thought (CoT) 390 methods in prompt. For the zero-shot method, we encourage the LLM to perform step-by-step text 391 generation by restricting and guiding the LLM to make the generated explanatory information as 392 structured and precise as possible, in order to achieve a better final result generation based on the 393 self-generated information. Although zero-shot VGRL is already fully interpretable, we still want to customize the interpretation in specific domains to ensure that the interpretation information is more 394 in line with the norms of the human mind and thus enhance the model's performance. Therefore, we 395 introduce the one-shot method by manually constructing a sample of the CoT, so that the model can 396 generate the interpretation information and the final output based on the sample. The motivation for 397 the one-shot approach is that we believe that the content generated by the LLM based on a sample 398 that conforms to the logic of the human mind will better contribute to the completion of the final 399 task. 400

401

403

404

405 406

407

408 409 410

411

412

413 414

415

416

417

418

419

428 429

430

#### 5 EXPERIMENTS

In this section, We will compare the performance of the VGRL framework with diverse backbone models for the TAG node classification task. We will answer the following questions:

- Q1: Can VGRL framework increase the performance of backbone models?
- **Q2:** Do each part of the VGRL framework play a positive role?

#### 5.1 BASELINE AND EXPERIMENT SETTING

We use two LLM-as-predictor models as backbones (Chen et al., 2024), and add our framework on top of them for comparisons. Information on our equipment can be found at Table 2.

- Node only: 'node only' refers to the features considering only the node itself, excluding any neighbor information.
- **Summary**: 'Summary' indicates that we used an independent LLM to summarize the node's *k*-hop information, which can be viewed as the introduction of an enhancer LLM for encoding the graph structure. The prompt for the enhancer LLM is shown in Table 1.

420 During the experiments, we used one-hop neighbor 421 information for summarization and set model tem-422 perature  $\tau = 0.1$  as default. Additionally, we intro-423 duced prior knowledge in our comparison by man-424 ually constructing prior knowledge as the initial op-425 timize  $\theta$  for iterative processing. And we setting a mini-batch training process with a batch size of 8, 426 i.e.  $|\mathcal{B}| = 8$ . 427

5.2 MAIN RESULTS (Q1)

Table 2: Information on our equipment

	Devices				
OS	Ubuntu 22.04.4 LTS x86_64				
Language	Python 3.10.14				
Frameworks	pytorch 2.4.0 + cuda 12.4				
CPU	Intel Xeon Silver 4310 (48) @ 3.300GHz				
GPU	3 * NVIDIA L20 (48G)				
Memory	128508MiB				

431 We conducted evaluations on the Cora TAG (McCallum et al., 2000) dataset (See AppendixB) by comparing our optimization iterative process with the baseline that excludes the VGRL framework

432 (Chen et al., 2024). The results are presented in Table 3. We extracted a subset of nodes from 433 the Cora dataset as our experimental data. For further steps, we blurred the concept of epochs and 434 treated each batch as a single step.

Fable 3: Node classifier	ssification	accuracy	for the Co	ra dataset		0.9 -
Core	w/ p	rior	w/o j	prior		0.8 -
Cola	zero-shot	one-shot	zero-shot	one-shot	Ś	
Node only	0.625	0.400	0.675	0.100	ura	07
Node only + VGRL	0.650	0.625	0.675	0.475	VCCI	0.1
Summary	0.650	0.550	0.700	0.475	st∕	
Summary + VGRL	0.800	0.700	0.875	0.700	Le	0.6 -
-	1					

Table 4: Ablation study on the Cora dataset, showing the effects of different variants base on Summary + VGRL on the accuracy performance

Cora Summary + VGRI	w/ prior		w/o prior	
Cora Summary + VORE	zero-shot	one-shot	zero-shot	one-shot
original method	0.800	0.700	0.875	0.700
w/o optimizer LLM	0.650	0.550	0.700	0.475
w/o summary LLM	0.650	0.625	0.725	0.625



Figure 3: Summary+VGRL Acc-Step

450 Our comparison reveals that our framework, through the iterative process, achieves better performance, demonstrating the effectiveness of the VGRL framework in representation learning. VGRL 452 gradually refines the label features through repeated iterations, as shown in Figure 3, which illustrates the change in test accuracy during the mini-batch iterations. Additionally, we used the open-453 source Llama3.1 8B model for all experiments, which not only significantly reduced costs but also 454 proved the optimization capability of the framework itself. 455

#### 5.3 ABLATION EXPERIMENTS (Q2)

We conducted ablation experiments on the Summary + VGRL architecture to assess the importance and relevance of each module. The results of the ablation experiments are shown in Table 4.

- w/o optimizer LLM: This variant removes the optimizer LLM, i.e., there is no iterative optimization process, which is equivalent to using the predictor LLM to make the final decision.
- w/o summary LLM: This variant removes the summary LLM, i.e., after each optimization update, instead of summarizing the information through the summary LLM, the results of a batch update are directly used in the next iteration.
- 5.4 CASE STUDY

435

443

444

445

446

447

448

449

451

456

457 458

459

460 461

462

463

464

465

466

467 468

469

470 To explore the impact of the VGRL framework on the TAG node classification task, we conducted an analysis of a particular training sample from the Cora dataset, as shown in Figure 4. In the paper 471 'Evolving Sensors in Environments of Controlled Complexity' the one-hop neighboring nodes all 472 have the label 'Genetic\_Algorithms' while the actual label of the node is 'Reinforcement\_Learning' 473 This heterogeneity can significantly disrupt the node's feature information during neighborhood ag-474 gregation, resulting in biased classification results. However, VGRL is able to effectively capture 475 unique characteristics of each category, using them as a basis for matching the node's own fea-476 tures. This addresses the issue of information corruption caused by the propagation mechanism in 477 heterogeneous graphs. 478

Moreover, in the Cora dataset, paper categories cannot be strictly divided into binary classes. It is 479 not uncommon for some nodes to belong to two categories simultaneously. In such cases, the label-480 feature matching mechanism proves to be more reasonable than the message-passing mechanism, 481 as it focuses more on the node's own information (as can be inferred from the formulation of  $\theta$ ). 482 Making judgments and decisions based on one's existing knowledge ( $\theta$ ) is the most fundamental 483 decision-making process for humans. 484

- 'Judgment' and 'Step-by-Step Analysis' represent the model's label matching process, which is 485 also human-readable and interpretable. Whether its the Predictor LLM's process of analyzing the
  - 9



Figure 4: Case study for one-shot wo prior Summary + VGRL: (1) The left figure shows the explanation information and prediction labels output by predictor LLM; (2) The right figure shows the optimization process of optimizer LLM for the predicted content of predictor LLM in the left figure.(3) The top-right figure shows an example of the one-hop neighbors of a predicted sample.

508

509

510

511

512

513

502

504

node's own features and supplementing it with neighborhood information, or the Optimizer LLM's analysis and adjustment of the two categories involved in classification errors, both demonstrate a complete and interpretable optimization process. The model explains each update iteration in detail, presenting it in human-readable language. With the help of the Summary LLM, the Predictor LLM and Optimizer LLM communicate and feedback effectively, ultimately constructing the best decision-making basis from scratch for the node classification task on the current dataset.

514 For a detailed training process see Appendix C to Appendix G.

THEORETICAL ANALYSIS

- 515
- 516
- 517 518

6

519 520

521

522

523

524

526

527

528

In this section, our goal is to demonstrate that the category descriptions generated by LLM can provide useful information for predicting label categories. Specifically, if the obtained category descriptions can faithfully represent the information of each category, then they are useful. At the same time, the LLM is non-redundant, as it can provide information that X cannot provide. Let  $\theta$ be the textual category descriptions generated by LLM;  $H_l$  are the embeddings of category from the LLM; X are the input of graph structure embeddings, y is the target and  $H(\cdot|\cdot)$  is the conditional entropy. The specific proof process can be found in Appendix A.

**Theorem.** Given the following conditions: 1) Fidelity:  $\theta$  can faithfully represent the information of  $H_l$  such that  $H(H_l|\theta) = \epsilon$ , with  $\epsilon > 0$ ; 2)Non-redundancy:  $H_l$  contains information not present in X, that is,  $H(y|X, H_l) = H(y|X) - \epsilon'$ , with  $\epsilon' > \epsilon$ . Then it follows that  $H(y|X, \theta) < H(y|X)$ .

529 530 531

#### 7 CONCLUSION

532 533

This paper introduces Verbalized Graph Representation Learning (VGRL), a novel approach to text-attributed graph learning that ensures full interpretability by representing learned parameters as textual descriptions instead of continuous vectors. This method enhances transparency and user understanding of the decision-making process, fostering greater trust in the model's outputs. While the current application is limited to foundational graph learning paradigms, VGRL shows promise for broader use in more complex models, offering potential advancements in explainable AI and graph-based learning systems.

### 540 REFERENCES

548

567

568

569

570

- Zhikai Chen, Haitao Mao, Hang Li, Wei Jin, Hongzhi Wen, Xiaochi Wei, Shuaiqiang Wang, Dawei
  Yin, Wenqi Fan, Hui Liu, et al. Exploring the potential of large language models (llms) in learning
  on graphs. ACM SIGKDD Explorations Newsletter, 25(2):42–61, 2024.
- Enyan Dai and Suhang Wang. Towards self-explainable graph neural network. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pp. 302–311, 2021.
- 549 Mingkai Deng, Jianyu Wang, Cheng-Ping Hsieh, Yihan Wang, Han Guo, Tianmin Shu, Meng Song,
  550 Eric P Xing, and Zhiting Hu. Rlprompt: Optimizing discrete text prompts with reinforcement
  551 learning. *arXiv preprint arXiv:2205.12548*, 2022.
- Xiaoxin He, Xavier Bresson, Thomas Laurent, Adam Perold, Yann LeCun, and Bryan Hooi. Harnessing explanations: Llm-to-lm interpreter for enhanced text-attributed graph representation learning. *arXiv preprint arXiv:2305.19523*, 2023.
- Sirui Hong, Xiawu Zheng, Jonathan Chen, Yuheng Cheng, Jinlin Wang, Ceyao Zhang, Zili Wang,
  Steven Ka Shing Yau, Zijuan Lin, Liyang Zhou, et al. Metagpt: Meta programming for multiagent collaborative framework. *arXiv preprint arXiv:2308.00352*, 2023.
- Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional net works. *arXiv preprint arXiv:1609.02907*, 2016.
- Guohao Li, Hasan Hammoud, Hani Itani, Dmitrii Khizbullin, and Bernard Ghanem. Camel: Communicative agents for" mind" exploration of large language model society. *Advances in Neural Information Processing Systems*, 36:51991–52008, 2023.
- Lu Li, Jiale Liu, Xingyu Ji, Maojun Wang, and Zeyu Zhang. Se-sgformer: A self-explainable signed
   graph transformer for link sign prediction. *arXiv preprint arXiv:2408.08754*, 2024a.
  - Shuang Li, Xavier Puig, Chris Paxton, Yilun Du, Clinton Wang, Linxi Fan, Tao Chen, De-An Huang, Ekin Akyürek, Anima Anandkumar, et al. Pre-trained language models for interactive decisionmaking. Advances in Neural Information Processing Systems, 35:31199–31212, 2022.
- Zekun Li, Baolin Peng, Pengcheng He, Michel Galley, Jianfeng Gao, and Xifeng Yan. Guiding large
   language models via directional stimulus prompting. *Advances in Neural Information Processing Systems*, 36, 2024b.
- Jacky Liang, Wenlong Huang, Fei Xia, Peng Xu, Karol Hausman, Brian Ichter, Pete Florence, and Andy Zeng. Code as policies: Language model programs for embodied control. In 2023 IEEE International Conference on Robotics and Automation (ICRA), pp. 9493–9500. IEEE, 2023.
- Ruotian Ma, Xiaolei Wang, Xin Zhou, Jian Li, Nan Du, Tao Gui, Qi Zhang, and Xuanjing Huang.
  Are large language models good prompt optimizers? *arXiv preprint arXiv:2402.02101*, 2024.
- Costas Mavromatis, Vassilis N Ioannidis, Shen Wang, Da Zheng, Soji Adeshina, Jun Ma, Han Zhao, Christos Faloutsos, and George Karypis. Train your own gnn teacher: Graph-aware distillation on textual graphs. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pp. 157–173. Springer, 2023.
- Andrew McCallum, Kamal Nigam, Jason Rennie, and Kristie Seymore. Automating the construction of internet portals with machine learning. *Information Retrieval Journal*, 3:127–163, 2000.
   www.research.whizbang.com/data.
- Lin Ni, Sijie Wang, Zeyu Zhang, Xiaoxuan Li, Xianda Zheng, Paul Denny, and Jiamou Liu. Enhancing student performance prediction on learnersourced questions with sgnn-llm synergy. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pp. 23232–23240, 2024.
- 593 Reid Pryzant, Dan Iter, Jerry Li, Yin Tat Lee, Chenguang Zhu, and Michael Zeng. Automatic prompt optimization with" gradient descent" and beam search. *arXiv preprint arXiv:2305.03495*, 2023.

639

640

- Chen Qian, Xin Cong, Cheng Yang, Weize Chen, Yusheng Su, Juyuan Xu, Zhiyuan Liu, and Maosong Sun. Communicative agents for software development. *arXiv preprint arXiv:2307.07924*, 6, 2023.
- 598 Yijian Qin, Xin Wang, Ziwei Zhang, and Wenwu Zhu. Disentangled representation learning with 599 large language models for text-attributed graphs. *arXiv preprint arXiv:2310.18152*, 2023.
- Chan Hee Song, Jiaman Wu, Clayton Washington, Brian M Sadler, Wei-Lun Chao, and Yu Su.
   Llm-planner: Few-shot grounded planning for embodied agents with large language models. In
   *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 2998–3009, 2023.
- Alessandro Sordoni, Xingdi Yuan, Marc-Alexandre Côté, Matheus Pereira, Adam Trischler, Ziang
   Xiao, Arian Hosseini, Friederike Niedtner, and Nicolas Le Roux. Deep language networks: Joint
   prompt training of stacked llms using variational inference. *arXiv preprint arXiv:2306.12509*, 2023.
- Jiabin Tang, Yuhao Yang, Wei Wei, Lei Shi, Lixin Su, Suqi Cheng, Dawei Yin, and Chao Huang.
   Graphgpt: Graph instruction tuning for large language models. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 491–500, 2024.
- Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua
   Bengio. Graph attention networks. *arXiv preprint arXiv:1710.10903*, 2017.
- Minh Vu and My T Thai. Pgm-explainer: Probabilistic graphical model explanations for graph neural networks. *Advances in neural information processing systems*, 33:12225–12235, 2020.
- Kuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. Self-consistency improves chain of thought reasoning in language models. *arXiv preprint arXiv:2203.11171*, 2022.
- Yifei Wang, Yupan Wang, Zeyu Zhang, Song Yang, Kaiqi Zhao, and Jiamou Liu. User: Unsupervised structural entropy-based robust graph neural network. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 37, pp. 10235–10243, 2023.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.
- Yuxin Wen, Neel Jain, John Kirchenbauer, Micah Goldblum, Jonas Geiping, and Tom Goldstein.
   Hard prompts made easy: Gradient-based discrete optimization for prompt tuning and discovery.
   *Advances in Neural Information Processing Systems*, 36, 2024.
- Jason Weston and Sainbayar Sukhbaatar. System 2 attention (is something you might need too).
   *arXiv preprint arXiv:2311.11829*, 2023.
- Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Shaokun Zhang, Erkang Zhu, Beibin Li,
  Li Jiang, Xiaoyun Zhang, and Chi Wang. Autogen: Enabling next-gen llm applications via multiagent conversation framework. *arXiv preprint arXiv:2308.08155*, 2023.
  - Tim Z Xiao, Robert Bamler, Bernhard Schölkopf, and Weiyang Liu. Verbalized machine learning: Revisiting machine learning with language models. *arXiv preprint arXiv:2406.04344*, 2024.
- Yaqi Xie, Chen Yu, Tongyao Zhu, Jinbin Bai, Ze Gong, and Harold Soh. Translating natural language to planning goals with large-language models. *arXiv preprint arXiv:2302.05128*, 2023.
- Junhan Yang, Zheng Liu, Shitao Xiao, Chaozhuo Li, Defu Lian, Sanjay Agrawal, Amit Singh,
  Guangzhong Sun, and Xing Xie. Graphformers: Gnn-nested transformers for representation
  learning on textual graph. Advances in Neural Information Processing Systems, 34:28798–28810,
  2021.

040	Songhua Yang, Hanjie Zhao, Senbin Zhu, Guangyu Zhou, Hongfei Xu, Yuxiang Jia, and Hongying
649	Zan. Zhongjing: Enhancing the chinese medical capabilities of large language model through
650	expert feedback and real-world multi-turn dialogue. In Proceedings of the AAAI Conference on
651	Artificial Intelligence, volume 38, pp. 19368–19376, 2024.

- Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Tom Griffiths, Yuan Cao, and Karthik
   Narasimhan. Tree of thoughts: Deliberate problem solving with large language models. Advances in Neural Information Processing Systems, 36, 2024.
- Yao Yao, Zuchao Li, and Hai Zhao. Beyond chain-of-thought, effective graph-of-thought reasoning
   in language models. *arXiv preprint arXiv:2305.16582*, 2023.
- Zhitao Ying, Dylan Bourgeois, Jiaxuan You, Marinka Zitnik, and Jure Leskovec. Gnnexplainer:
   Generating explanations for graph neural networks. *Advances in neural information processing* systems, 32, 2019.
- Hao Yuan, Jiliang Tang, Xia Hu, and Shuiwang Ji. Xgnn: Towards model-level explanations of
   graph neural networks. In *Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining*, pp. 430–438, 2020.
- Zaixi Zhang, Qi Liu, Hao Wang, Chengqiang Lu, and Cheekong Lee. Protgnn: Towards self explaining graph neural networks. In *Proceedings of the AAAI Conference on Artificial Intelli- gence*, volume 36, pp. 9127–9135, 2022a.
- Zeyu Zhang, Jiamou Liu, Kaiqi Zhao, Song Yang, Xianda Zheng, and Yifei Wang. Contrastive learn ing for signed bipartite graphs. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 1629–1638, 2023a.
- <sup>672</sup> Zeyu Zhang, Jiamou Liu, Xianda Zheng, Yifei Wang, Pengqian Han, Yupan Wang, Kaiqi Zhao, and
  <sup>673</sup> Zijian Zhang. Rsgnn: A model-agnostic approach for enhancing the robustness of signed graph
  <sup>674</sup> neural networks. In *Proceedings of the ACM Web Conference 2023*, pp. 60–70, 2023b.
- <sup>676</sup> Zhuosheng Zhang, Aston Zhang, Mu Li, and Alex Smola. Automatic chain of thought prompting in large language models. *arXiv preprint arXiv:2210.03493*, 2022b.
- Yongchao Zhou, Andrei Ioan Muresanu, Ziwen Han, Keiran Paster, Silviu Pitis, Harris Chan, and Jimmy Ba. Large language models are human-level prompt engineers. *arXiv preprint arXiv:2211.01910*, 2022.
- Jason Zhu, Yanling Cui, Yuming Liu, Hao Sun, Xue Li, Markus Pelger, Tianqi Yang, Liangjie
   Zhang, Ruofei Zhang, and Huasha Zhao. Textgnn: Improving text encoder via graph neural
   network in sponsored search. In *Proceedings of the Web Conference 2021*, pp. 2848–2857, 2021.

702 APPENDIX 703 704 THEORETICAL ANALYSIS А 705 706 In this section, our goal is to demonstrate that the category descriptions generated by LLM can 707 provide useful information for predicting label categories. We formulate our theorem as follows: 708 709 **Theorem.** Given the following conditions: 710 1) Fidelity:  $\theta$  can faithfully represent the information of  $H_l$  such that 711 712  $H(H_l|\theta) = \epsilon, \epsilon > 0;$ (5)713 2)Non-redundancy:  $H_1$  contains information not present in X, that is 714 715  $H(y|X, H_l) = H(y|X) - \epsilon', \epsilon' > \epsilon;$ (6)716 Then we can obtain: 717  $H(y|X, \theta) < H(y|X).$ (7)718 719 where  $\theta$  be the textual category descriptions generated by LLM;  $H_l$  are the embeddings of category 720 from the LLM; X are the input of graph structure embeddings, y is the target and  $H(\cdot|\cdot)$  is the 721 conditional entropy. 722 723 *Proof.* We aim to demonstrate that  $H(y|X, \theta) < H(y|X)$ , the process is following: 724 Start with: 725  $H(y|X,\theta)$ (8) 726 We decompose the original expression Equation 8 into two parts based on the properties of entropy: 727  $H(y|X,\theta) = H(y|X,H_l,\theta) + I(y;H_l|X,\theta)$ (9)728 729 Based on the definition of mutual information, we can obtain: 730  $I(y; H_l | X, \theta) = H(H_l | X, \theta) - H(H_l | X, \theta, y)$ (10)731 732 Due to the non-negativity of conditional entropy, we have: 733  $I(y; H_l | X, \theta) < H(H_l | X, \theta)$ (11)734 735 By substituting Equation 11 into Equation 9, we further obtain: 736  $H(y|X,\theta) \le H(y|X,H_l,\theta) + H(H_l|X,\theta)$ (12)737 738 When conditional variables decrease, the conditional entropy increases; so we have: 739  $H(y|X,\theta) \le H(y|X,H_l) + H(H_l|\theta)$ (13)740 741 Applying the two aforementioned conditions and substituting Equations 5 and 6 into Equation 12, 742 we can obtain:  $H(y|X,\theta) \le H(y|X) + \epsilon - \epsilon' < H(y|X)$ 743 (14)744 The conclusion is thus proven. 745 746 В DATASET DESCRIPTION 747 748 Cora (McCallum et al., 2000): The Cora dataset consists of Machine Learning papers. These pa-749 pers are classified into one of the following seven classes: Case\_Based, Genetic\_Algorithms, Neu-750 ral\_Networks, Probabilistic\_Methods, Reinforcement\_Learning, Rule\_Learning, Theory. The papers 751 were selected in a way such that in the final corpus every paper cites or is cited by atleast one other 752 paper. There are 2708 papers and 5429 links in the whole corpus. 753 754 755

#### 756 C ONE-SHOT COT

### The one-shot example.

one-shot predictor LLM CoT
Paper information:
(Paper Title: Case-Based Planning to Learn ) (Abstract: Learning can be viewed as a problem of planning a series of modifications to memory. We
adopt this view of learning and propose the applicability of the case-based planning methodology to the task of planning to learn. We argue that relatively simple, fine-grained primitive inferential operators
are needed to support flexible planning. We show that it is possible to obtain the benefits of case-based reasoning within a planning to learn framework.)
(Neighbour Summary: Ine papers cited in this essay discuss the challenges and limitations of artificial intelligence, specifically in the areas of case-based reasoning and inference control. The first paper presents
by reasoning from scratch and then stored as cases for future adaptation problems are initially solved the problem of combinatorial explosion of inferences and proposes a method to generate explicit desires
for knowledge to control inference and facilitate goal pursuit. Both papers highlight the importance of knowledge acquisition and inference control in artificial intelligence.
Common points that reflect the category of this paper include the focus on case-based reasoning, the need for knowledge acquisition and inference control, and the emphasis on artificial intelligence.)
Judgment:
The paper titled "Case-Based Planning to Learn" presents the idea that learning can be viewed as a problem of planning modifications to memory, and it applies case-based reasoning to support flexible
planning in learning. It emphasizes the reuse of past cases to inform future planning, which aligns with case-based methodologies.
The core of the paper discusses case-based reasoning, which involves using past experiences (in the form of cases) to guide future learning and problem-solving. The approach focuses on planning based on previously
solved cases and adapting them to new scenarios, which is a hallmark of Case-Based methodologies. The abstract and the cited papers highlight the importance of case retrieval and adaptation processes for headling large in and encouring both entry large track to Case Paral encouring the second encouring the second
The neighbour summary further supports the categorization, discussing the role of case adaptation knowledge and its use in addressing new problems, aligning with the Case-Based category.
Final decision: <case_based></case_based>
one-shot Optimizer LLM CoT
Paper Information:
(Paper Title: Case-Based Planning to Learn )
(Abstract: Learning can be viewed as a problem of planning a series of modifications to memory. We adopt this view of learning and propose the applicability of the case-based planning methodology to the
task of planning to learn. We argue that relatively simple, fine-grained primitive inferential operators are needed to support flexible planning. We show that it is possible to obtain the benefits of case-based
reasoning within a planning to learn framework.) (Neighbour Summary: The papers cited in this essay discuss the challenges and limitations of artificial intelligence provides the paper of the paper is based provides and information of the fact paper provides the second secon
a new approach to acquiring case adaptation knowledge, where adaptation problems are initially solved by reasoning from scratch and then stored as cases for future adaptation. The second paper addresses
the problem of combinatorial explosion of inferences and proposes a method to generate explicit desires for knowledge to control inference and facilitate goal pursuit. Both papers highlight the importance of
knowledge acquisition and inference control in artificial intelligence. Common points that reflect the category of this paper include the focus on case-based reasoning, the
need for knowledge acquisition and inference control, and the emphasis on artificial intelligence.)
<case based=""></case>
Paper true category:
<case_based></case_based>
Step-by-Step Analysis:
1. **Model Judgment and True Category Comparison** - **Model Judgment Category*: * <case_based>* **True Category*: *: * Case_Based&gt;*</case_based>
The model has correctly classified this paper under the * <case_based>* category. Since both the model's indement and the true category match we more on to analyzing whether the original indement hasis for</case_based>
* <case based="">* is accurate or needs to be updated based on this paper's information. 2. **Examination of the Paper Information (Title, Abstract, Neighbour Summary)**</case>
<ul> <li>**Paper Title**: *Case-Based Planning to Learn*</li> <li>The title directly suggests the focus on *Case-Based* methods. Specifically, it highlights the use of</li> </ul>
*planning* in conjunction with *case-based reasoning* to facilitate learning. - **Abstract**:
<ul> <li>Ine abstract provides clear evidence that the paper is centered around "case-based reasoning", as it proposes the use of a "case-based planning methodology" to plan learning processes. It also discusses storing near solutions for future use, which is constrait to "near barrier".</li> </ul>
<ul> <li>The mention of "modifications to memory" and "benefits of case-based reasoning".</li> <li>The mention of "modifications to memory" and "benefits of case-based reasoning" reinforces the paper's focus on adapting previous experiences to solve new problems, which is a key aspect of "<case based="">"</case></li> </ul>
reasoning. - **Neighbour Summary**:
<ul> <li>The neighbouring papers also focus on "case-based reasoning", "knowledge acquisition", and "inference control". These are essential to "<case_based>" reasoning, as they emphasize solving new problems by</case_based></li> </ul>
leveraging past experiences and stored cases. 3. **Evaluation of the Existing Judgment Basis for <case_based>**</case_based>
<ul> <li>*If the paper discusses the use of past experiences, memory-based techniques, or case retrieval and adapted in processor to solve one upphleme algorithm is a solver based techniques.</li> </ul>
acaptation processes to solve new problems, Classify it as <case_dased>." The paper fits this description well: -*"Use of past experiences*": The paper discusses retrieving and using past cases (i.e., stored solutions)</case_dased>
to plan learning processes. - **Memory-based techniques**: The reference to *modifications to memory* and storing past daptations
falls under memory-based techniques. - **Case retrieval and adaptation**: The paper directly mentions using case-based reasoning within a
planning framework, which includes adapting stored cases to new learning challenges. 4. **Determining the Need for Modifications**
The current judgment basis for * <case_based>* is well-aligned with the content of this paper. The focus on using past experiences, memory modifications, and case adaptation processes are clearly articulated in</case_based>
the abstract and neighbor summary. - **No new features need to be added** to the * <case_based>* category based on this paper, as it fits perfectly within the existing framework.</case_based>
Updated judgment basis:
<newpattern>Case_Based: If the paper discusses the use of past experiences, memory-based</newpattern>
techniques, or case retrieval and adaptation processes to solve new problems, classify it as $<\!Case\_Based>.$

#### TRAINING DETAIL FOR SUMMARY + VGRL D

#### D.1 ONE-SHOT W/O PRIOR SUMMARY + VGRL STEP 1

ck provided by the optimization model suggests that the individual categories of papers have inique characteristics: the information given which category the  $\ell$ -11......

The building provided by this eminantian model argueds that the individual calcupation of papers have adding from the information pipers which category the following care yoldshape. We can be store provide the distribution of the paper fits into each extegory. First, phase analyse which the paper matches category of 200° and 200° and

Paper information: Paper This Structure Propositionalization of Non-Determinate Background Kasoledge ) (Alstract II: is a well-known free that propositional intenting algorithms regard "good" however, it good faster by faster and a structure of the proposition of the proposition of proposition of the proposition

(and). Perturbatives experiments are forwards, and support the view that this approach up remaining. (Singhbor Smarrows): more diverse views techniques and approaches the field of Role Learning, perficially in Inductive Lagie Pergramming (LP). This first paper re-approace the development of techniques in the viewstrag ideal trains and introduces all horizontal arrows. California (LM) is a development of the strain of the techniques in the strain of the strain the frameworks of the strain strain of the strain of

Judgement: The paper titled "Stochastic Propositionalization of Non-Determinate Background Knowledge" discusses for the order of Stochastic Propositionalization of Non-Determinate Background Knowledge" discusses for the order of the proposition of the order of

Now that you have some descriptions, which will be used as rubrics for the classification task, you need to summarize and refine them for each category to find the best way to express them. Here are the descriptions:

to examine and refine them for each enterprot for fifth the hort way to express them. Markowski and the stress of the stress of enterprot the following more behavior: " "Conse, Boards". If the paper discusses the use of part expressions, enterprot the stress of the

Note: Please OKLY summarize each category without omissions and NOTHING ELSE! And each category is output in the following format: (Case Based): Papers that include [your summary] should be categorized as <Case Based>. (Genetic\_Algorithms>: Papers that include [your summary] should be categorized as <Genetic\_Algorithms>.

Pinane brogin with < CTART SUMMARY </p>
CART SUMMARY 
Char Endstrip in the 
Cara Endstrip 
Construction 
Constructio

. at\_Learning>: Papers that include [your su

na dr. Algoritania : Papers that include [your summary] should be categorized as <br/>Networks>.<br/>robalilistic\_Methods>: Papers that include [your summary] should be categorized as <br/>Networks>.<br/>robalilistic\_Methods>: Papers that include [your summary] should be categorized as <br/>Probabilis\_Methods>:

y] should be ca

Final decision: <Rule\_Learning>

<Theory>: Papers ti or mathematical mo <END\_SUMMARY:

The categorization model performed the judgment of paper categories by using the following features nainput to each category of papers as the basis for the judgment. Judge from the information given which category the following easay belongs to. I will provide the title, abstract, citation summary information of your paper, the categories judged by the classification model, and the real categories of the paper, and ank you to verify that the basis of judgment for the corresponding categories is accurate. First of all, plasma compare which categories provided by the model and the scitual categories match, first of all, plasma compare whether the categories provided by the model and the scitual categories match, you don't need to change anything; if it doesn't match, plasma analyze why the model may classify this paper into the category based on the original judgment basis corresponding to the incorrect category, and then plasma summarize the modifications and adjustments to the original judgment bases of the two the true category, or adjust the basis of judgment according to what you think is correct. Describe each step of the reasoning process in detail, and give the final updated basis of judgment, bases of judgment. For example:

Here is a one-shot example; for more details, please refer to the appendix

Now analyze the given paper:

The number will given paper: Paper information Paper Title: Stochastic Propositionalization of Non-Determinate Background Knowledge ) (Albetract: It is a welk-known fact that propositional learning indeprithms require "good" features to perform well in practice. So a major step in data engineering for inductive learning is the construction of pool features by domain experts. These features often represent properties of structure objects, where valuation and the structure of the structure of the represent properties of structure objects, where valuation the process of "feature engineering", we devised an algorithm that searches for features which are defined by such abstructures. The algorithm stochastically conduct a top-down search for frat-order damase, where each chance represents a binary feature. It differs from existing algorithms in that its search (size). Preliminary experiments are favorable, and support the view that this approach is provided in this ease, discuss various techniques and approaches in the field of Rule Learning of techniques for inverting deduction and introduces Mode-Directed Inverse Entailment (MDIE) as a enceralisation and enhancement of previous approaches. The second paper proposes an extension of the feature-vector representation to allow the value of a feature to be a set of strings, which can be channed SPOIL that use as atochastic search method to alleviate the local optimization problem in greedy algorithms. Overall, these papers highlight the importance of efficient and effective techniques in Rule Learning and LP) (step-barries) Step-by-Step Analysis:

Step-by-Step Analysis:

Functional Start Star

Updated judgment bi

<NewPattern>Rule\_Learning: If the paper discusses the construction of rules, propositional-ization, or the use of stochastic methods in the context of inductive learning, classify it as <Rule Learning>.</RevPattern>

#### 864 D.2 ONE-SHOT W/O PRIOR SUMMARY + VGRL STEP 2

866		one-shot optimizer LLM CoT wo prior Step 2
867		The categorization model performed the judgment of paper categories by using the following features
868	one-shot predictor LLM CoT wo prior Step 2	unique to each category of papers as the basis for the judgment: <case based="">: Papers that discuss the use of past experiences, memory-based techniques, case</case>
869	In a methanic provided by the dynamization modes suggests that the individual categories of papers have their own usinglue characteristics: <case based="">: Papers that discuss the use of past experiences, memory-based techniques, case retrieval, and adaptation processes to solve new problema, and emphasize the importance of explanation</case>	retrieval, and adaptation processes to solve new problems, and emphasize the importance of explanation in goal-driven learning, including introspection and adaptation of explanation strategies. <genetic_algorithms>: Papers that discuss the use of evolutionary principles, genetic algorithms,</genetic_algorithms>
870	in goar-invine neishing, including introduction and analyticition of explanation strategies. <constit: algorithms,<br="" algorithms:="" discuss="" evolutionary="" genetic="" of="" papers="" principles,="" that="" the="" use="">mutation, crossover, selection, and their applications, implementations, or comparison with other optimization methods.</constit:>	optimization methods. <neural_networks>: Papers that discuss artificial neural networks, their architecture, training methods, applications, connectionist approaches, radial basis function networks, and the convergence of the</neural_networks>
871	<wwind "presentes"="" a="" appresented="" be="" is="" of="" set="" td="" the="" the<="" to=""><td>backpropagation algorithm. <probabilistic_methods>: (No description available) <reinforcement learning="">: (No description available)</reinforcement></probabilistic_methods></td></wwind>	backpropagation algorithm. <probabilistic_methods>: (No description available) <reinforcement learning="">: (No description available)</reinforcement></probabilistic_methods>
872	<reiniotesment _learning="">: (No description available) <reis_learning>: Papers that discuss the construction of rules, propositionalization, and the use of stochastic methods in the context of inductive learning. <theoryy: algorithms,="" as="" aspects="" complexity,<="" computer="" discuss="" of="" p="" papers="" science,="" such="" that="" theoretical=""></theoryy:></reis_learning></reiniotesment>	<rule_learning>: Papers that discuss the construction of rules, propositionalization, and the use of stochastic methods in the context of inductive learning. <theory>: Papers that discuss theoretical aspects of computer science, such as algorithms, complexity.</theory></rule_learning>
873	or mathematical models. I will provide you with the title, abstract, and citation summary of your paper and ask you to step-by-step determine if the paper fits into each category. First, please analyze whether the paper matches category	or mathematical models. I will provide the title, abstract, citation summary information of your paper, the categories judged by
874	<come_massed>. It it does, please explain how it matches; it it doesn't, please point out where it doesn't. Then please compare the categories <cometi_algorithms> and vice versa. After comparing all the categories, please decide which category the paper fits better, and give a final classification decision, please enclose the final decision in &lt;&gt;&gt;</cometi_algorithms></come_massed>	the classification model, and the real categories of the paper, and ask you to verify that the basis of judgment for the corresponding categories is accurate. First of all, please compare whether the categories provided by the model and the actual categories match.
875	Your analyse the monimized norm the green paper. Here is a one-shot example, for more details, please refer to the appendix.	If it matches, you will directly analyze whether you need to add new judgment basis to the corresponding category based on the information and original judgment basis of the paper, if you need to add it, if not, you don't need to change anything; if it doesn't match, please analyze why the model may classify this
876	(Paper Title: Learning from positive data.) (Abstract: Gold showed in 1097 that not even regular grammars can be exactly identified from positive examples alone. Since it is known that children learn natural grammars almost exclusively from positive examples. Gold's result has been used as a theoretical support for Chomeky's theory of innate human	paper into the category based on the original judgment basis corresponding to the incorrect category, and then please summarize the modifications and adjustments to the original judgment bases of the two categories, you can choose to remove matches for this paper in the wrong category, add unique features in the second sec
877	linguistic abilities. In this paper new results are presented which show that within a Bayesian framework not only grammars, but also logic programs are learnable with arbitrarily low expected error from positive examples only. In addition, we show that the upper bound for expected error of a learner which maximizes the Bayes' posterior probability when learning from positive examples is within a small additive term of one	the true category, or adjust the basis of judgment according to what you think is correct. Describe each step of the reasoning process in detail, and give the final updated basis of judgment, enclosing the final decision in <newpattern></newpattern> . For example:
878	which does the same from a mixture of positive and negative examples. An Inductive Logic Programming implementation is described which avoids the pitfall of greedy search by global optimization of this function during the local construction of individual clauses of the hypothesis. Results of testing this is the provided of the same search of the hypothesis.	New sector state and the sector state and the sector state and the sector state sec
879	implementation on Artificially-generated data-sets are reported. Insee results are in agreement with the theoretical predictions.) (Neighbour Summary: The papers cited in this essay discuss the limitations of current inductive logic programming systems	Now analyze the given paper:
880	in handling noise and learning recursive predicates. A new framework for learning from noisy data and fixed example size is presented, which incorporates a Bayasian heuristic for finding the most probable hypothesis. This approach is implemented in an LP system called Lime, which is shown to handle noise better than other systems like FOLL and PROGOL, and is capable of learning from only positive or	(Paper Title: Learning from positive data ) (Abstract: Gold showed in 1967 that not even regular grammars can be exactly identified from positive examples alone. Since it is known that children learn natural grammars almost exclusively from positives
881	negative data. Common points that reflect the category of this paper include: - Handling noise in inductive logic programming systems - Learning recursive predicates	examples, Gold's result has been used as a theoretical support for Chomaky's theory of innate human linguistic abilities. In this paper new results are presented which show that within a Bayesian framework not only grammars, but also logic programs are learnable with arbitrarily low expected error from positive
882	Improving the performance of ILP systems     Developing new frameworks for learning from noisy data.)     Judgment:	examples only. In addition, we show that the upper bound for expected error of a learner which maximises the Bayes' posterior probability when learning from positive examples is within a small additive term of one which does the same from a mixture of positive and negative examples. An Inductive Logic Programming
883	The paper titled "Learning from positive data" discusses the theoretical and practical aspects of learning from positive examples alone, which is a key concept in genetic algorithms and evolutionary computation. The paper presents new results on the learnability of logic programs from positive examples within a	implementation is described which avoids the pittails of greedy search by global optimisation of this function during the local construction of individual clauses of the hypothesis. Results of testing this implementation on artificially-generated data-sets are reported. These results are in agreement with the dependent of the second sec
884	Daywinki transwork, which is a common approach in genetic algorithms. The abstract and the cited papers highlight the importance of handling noise and learning recursive predicates, both of which are central to genetic algorithms and svolutionary computation. The neighbour summary further apport the categorization, discussing the limitations of current ILP of the state of the	(Neighbour Summary: (Neighbour Summary: The papers cited in this easy discuss the limitations of current inductive logic programming systems in handling noise and learning recursive predicates. A new framework for learning from noisy data and
885	provide and the weekpanets of new frameworks of rearing from noisy take, which is a key aspect of genetic algorithm. Final decision:	fixed example size is presented, which incorporates a Bayesian heuristic for finding the most probable hypothesis. This approach is implemented in an ILP system called Lime, which is shown to handle noise better than other systems this FOUL and BROGOL and is campled of learning from only notifying or
886	<genetic_algorithms></genetic_algorithms>	Common points that reflect the category of this paper include:
887	one-shot summary LLM CoT we prior Step 2	Inflamma noise in inductive logic programming systems     Learning recursive predicates     Improving the performance of ILP systems
888	Now that you have some descriptions, which will be used as rubrics for the classification task, you need to summarize and refine them for each category to find the best way to express them. Here are the descriptions:	<ul> <li>Developing new frameworks for learning from noisy data.)</li> <li>Model judgment category:</li> <li>Genetic Algorithms</li> </ul>
880	<case baxed="">: If the paper discusses the use of past experiences, memory-based techniques, or case retrieval and adaptation processes to solve new problems, classify it as <case baxed="">. If the paper discusses the use of past experiences, memory-based techniques, or case retrieval and adaptation processes to solve new problems, classify it as <case baxed="">.</case></case></case>	Paper true category: Theory
800	Cenetic_Algorithms.>: If the paper discusses the use of evolutionary principles, genetic algorithms, mutation, "crossover, selection, and their applications, implementations, or comparisons with other optimization methods, classify it as <genetic_algorithms.>: Exclude papers that discuss learning from positive data. Bayesian frameworks or ILP systems.</genetic_algorithms.>	Step-by-Step Analysis: 1. **Model Judgment and True Category Comparison**
901	<neural networks="">: Papers that discuss artificial neural networks, their architecture, training methods, applications, connectionist approaches, radial basis function networks, and the convergence of the backpropagation algorithm.</neural>	- **Model Judgment Category**: * <genetic_algorithms>* - **True Category**: *<theory>* The model has incorrectly classified this paper under the *<genetic_algorithms>* category. The true</genetic_algorithms></theory></genetic_algorithms>
000	<reinforcement learning="">: (No description available) <rule learning="">: Papers that discuss the construction of rules, propositionalization, and the use of stochastic methods in the context of inductive learning.</rule></reinforcement>	<pre>category is *<theory>*. We need to analyze why the model might have made this mistake and adjust the judgment basis accordingly. 2. **Examination of the Paper Information (Title, Abstract, Neighbour Summary)**</theory></pre>
092	< ready >= it use paper inscripts interactive interactions appears or complete scence, such as anyorhims, topologicality, or mathematical models, especially in the context of machine learning and feature selection, classify it as  Theory>. If the paper discusses theoretical aspects of computer science, such as algorithms, complexity, or mathematical models, classify it as  The paper discusses theoretical aspects of computer science, such as algorithms, complexity, or mathematical models, classify it as	<ul> <li>**Paper Title**: "Learning from positive data"</li> <li>The title does not directly suggest a focus on "Genetic_Algorithms", but rather on learning from positive data, which could be related to various areas of machine learning and theory.</li> </ul>
893	science, such as algorithms, complexity, or mathematical models, classity it as <theory>. If the paper discusses theoretical aspects of computer science, such as algorithms, complexity, or mathematical models, classify it as <theory>. If the paper discusses theoretical aspects of computer science, such as algorithms, complexity, or mathematical models, classify it as <theory>.</theory></theory></theory>	<ul> <li>***Abstract**:</li> <li>The abstract discusses the learnability of logic programs and grammars from positive examples within a Bayesian framework. It also mentions the implementation of an Inductive Logic Programming system and</li> </ul>
894	Note: Please ONLY summarize each category without omissions and NOTHING ELSE! And each category is output in the following format: $: Papers that include [your summary] should be categorized as .$	its performance on artificial data-sets. There is no mention of genetic algorithms, mutation, crossover, selection, or evolutionary principles. - **Neighbour Summary**:
895	<genetic_algorithms>: Papers that include [your summary] should be categorized as <genetic_algorithms>. <neural_networke>: Papers that include [your summary] should be categorized as <neural_networke>. <probabilistic methods="">: Paper shat include [your summary] should be categorized as <probabilities.< p=""></probabilities.<></probabilistic></neural_networke></neural_networke></genetic_algorithms></genetic_algorithms>	<ul> <li>The neighbouring papers focus on the limitations of current inductive logic programming systems, the development of new frameworks for learning from noisy data, and the improvement of ILP systems. These topics are more aligned with theoretical aspects of computer science and machine learning than with</li> </ul>
896	tic_Methods>. - Reinforcement_Learning>: Papers that include [your summary] should be categorized as <reinforce- ment_Learning&gt;: - Rule_Learning&gt;: Papers that include [your summary] should be categorized as <rule_learning>.</rule_learning></reinforce- 	genetic algorithms. 3. **Evaluation of the Existing Judgment Basis for <genetic_algorithms>** The current judgment basis for *<genetic_algorithms>* is as follows:</genetic_algorithms></genetic_algorithms>
897	<theory>: Papers that include (your summary) should be categorized as <theory>. Please begin with <start_summary> <start_summary></start_summary></start_summary></theory></theory>	<ul> <li>*If the paper discusses the use of evolutionary principles, genetic algorithms, mutation, crossover, selection, and their applications, implementations, or comparisons with other optimization methods, classify it as <genetic_algorithms>.*</genetic_algorithms></li> </ul>
898	<case based="">: Papers that discuss the use of past experiences, memory-based techniques, or case retrieval and adaptation processes to solve new problems should be categorized as &lt;. <genetic algorithms="">: Papers that discuss the use of evolutionary principles, genetic algorithms mutation, "crossover, selection, and their applications, implementations, or comparisons with other</genetic></case>	The paper does not fit this description: - **Evolutionary principles**: There is no mention of evolutionary principles or genetic algorithms in the abstract or neighbor summary.
899	optimization methods, excluding papers that discuss learning from positive data, Bayesian frameworks, or ILP systems, should be categorized as <genetic "algorithmy<br=""><neural architecture,="" artificial="" discuss="" methods,<br="" networks):="" networks,="" neural="" papers="" that="" their="" training="">applications, connectionist approaches, radial basic function networks, and the convergence of the</neural></genetic>	<ul> <li>**Genetic algorithms**: The paper does not discuss genetic algorithms or any of their components.</li> <li>4. **Determining the Need for Modifications**</li> <li>The current judgment basis for *<genetic algorithms="">* is not aligned with the content of this paper.</genetic></li> </ul>
900	backpropagation algorithm should be categorized as <neural_networks>. <probabilitis_methods>:Papers that discuss probabilistic approaches, statistical models, or uncer- tainty management is machine learning should be categorized as <probabilistic_methods>.</probabilistic_methods></probabilitis_methods></neural_networks>	The focus on learning from positive data, Bayesian frameworks, and ILP systems does not match the criteria for * <genetic_algorithms>*. - *"Remove the matches for this paper in the wrong category*": The paper should not be classified under</genetic_algorithms>
901	Chemiorchamics_chaming>: 1 apers' una 'uncost use use or trai and wron', reducts, penators, or other feedback mechanisms to learn from interactions with an environment should be categorized as <reinforcement learning="">: Agers that discuss the construction of rules, propositionalization, and the use of</reinforcement>	* <genetic_algorithms>*. *.**Add unique features in the true category**: The paper should be classified under *<theory>* because it discusses theoretical aspects of computer science, such as the learnability of logic programs</theory></genetic_algorithms>
902	reconsute metnoars in the context of inductive learning should be categorized as <rule learning="">. <theory>: Papers that discuss theoretical aspects of computer acinese, such as algorithm, complexity, mathematical models, or feature selection, especially in the context of machine learning, should be categorized as <theory>.</theory></theory></rule>	and grammars within a Bayesian framework. - **Adjust the basis of judgment**: The judgment basis for * <genetic _algorithms="">* should be updated to exclude papers that discuss learning from positive data, Bayesian frameworks, or ILP systems.</genetic>
903		Updated judgment basis:
904		<newpattern>Genetic_Algorithms: If the paper discusses the use of evolutionary principles, genetic algorithms, mutation, crossover, selection, and their applications, implementations, or comparisons with other optimization methods, classify it as <genetic_algorithms>. Exclude papers that discuss learning</genetic_algorithms></newpattern>
905		from positive data, Bayesian frameworks, or ILP systems.
906		
907		

#### 918 D.3 ONE-SHOT W/O PRIOR SUMMARY + VGRL STEP 80

one-shot predictor LLM CoT we prior Step 80	
The feedback provided by the optimization model suggests that the individual categories of papers have their own unique characteristics:	
<case based="">: Papers that discuss the use of past experiences, memory-based techniques, case retrieval, adaptation processes, continuous task domains, robotic navigation, knowledge compilation, dynamic exclusions and resulting in the domains control of the second memory of the second part of the second how the second secon</case>	
selection and moduleation of behavior assembliques, and case-based reasoning transvers should be categorized as <case based="">. <genetic algorithms="">: Papers that discuss genetic algorithms, evolutionary processes, artificial life, theoretical biology, simulation, evolving neural networks, adapting to changing environments,</genetic></case>	
optimization techniques involving genetic algorithms, and applications in machine learning, autonomous vehicles, and robotics, excluding contensitivity constitution and robustness of induced models against cost changes, should be categorized as <genetic algorithms="">. <td>one-shot optimizer LLM CoT wo prior Step 2</td></genetic>	one-shot optimizer LLM CoT wo prior Step 2
splications, connectionist approaches, neurobiology and cognitive psychology links, model calibration, learning parameter values, neural structures and functions, probabilistic methods, generative models, memory-based methods, approximation using radial basis functions, learning from prior knowledge.	The categorization model performed the judgment of paper categories by using the following fea
highly nonlinear models, pattern recognition, stability, and control in nonlinear systems should be categorized as <neural networks="">. <probabilistic angreaches="" methods="" networks.="" neural="" of="" probabilistic="" solve<="" substitution="" td="" the="" to=""><td>unique to each category of papers as the basis for the judgment: <case_based>: Papers that discuss the use of past experiences, memory-based techniques, case retri</case_based></td></probabilistic></neural>	unique to each category of papers as the basis for the judgment: <case_based>: Papers that discuss the use of past experiences, memory-based techniques, case retri</case_based>
productives approaches so usual networks, and the approaches of a solution of photoshilatic Methods. expected and the context of neural networks where the approaches and the solution of the device expected and the solution of the soluti	adaptation processes, continuous task domains, robotic navigation, knowledge compilation, dyna selection and modification of behavior assemblages, and case-based reasoning framework should categorized as <case based="">.</case>
stochastic systems, adapting traditional RL methods, exploration and navigation costs, using learned distances to guide exploration decisions, optimizing exploration based on expected benefits and costs, adapting to dynamic environments, using feedback mechanisms to guide decision-making, coordinat- ing reactive behaviors, using neural naturative as parts of a control asystem and temporal difference	<genetic_algorithms>: Papers that discuss genetic algorithms, evolutionary processes, artif life, theoretical biology, simulation, evolving neural networks, adapting to changing environm- ontimization techniques involving generic algorithms, and applications in machine learning autonom</genetic_algorithms>
learning, excluding theoretical foundations and proof-based learning, should be categorized as <rein- forcement_learning&gt;. <rule_learning>: Papers that discuss constructing rules, adapting methods for attribute estimation,</rule_learning></rein- 	vehicles, and robotics, excluding cost-sensitive classification and robustness of induced models agr cost changes, should be categorized as <genetic algorithms="">.</genetic>
non-myopic learning of regression trees, transforming regression algorithms, ordinal classification tasks, improving learning algorithms, addressing concept overlap problems, feature selection or greedy algorithms, employing stable models as background knowledge for a top-down ILP learner, improving existing machine learning algorithms, addressing concept overlap, using stochastic complexity formulas.	applications, connectionist approaches, neurobiology and cognitive psychology links, model calibra learning parameter values, neural structures and functions, probabilistic methods, generative mo
or employing simulated annealing-based beam search should be categorized as <rule larring="">. <theory>: Papers that discuss theoretical aspects of learning, implications of findings on learning processes, foundational principles of machine learning, decision trees, ensemble learning, efficiency</theory></rule>	memory-based methods, approximation using radial basis functions, learning from prior knowle highly nonlinear models, pattern recognition, stability, and control in nonlinear systems should categorized as <neural networks="">.</neural>
improvements at a primary notus, or practical applications of these theoretical aspects should be categorized as <theory>. I will provide you with the title, abstract, and citation summary of your paper and ask you to step-by-step</theory>	<probabilistic_methods>: Papers that discuss Bayesian inference, priors over model parame probabilistic approaches to neural networks, and the application of probabilistic methods to s practical problems in the context of neural networks should be categorized as <probabilistic metho<="" td=""></probabilistic></probabilistic_methods>
determine if the paper fits into each category. First, please analyze whether the paper matches category <case basel="">. If it does, please explain how it matches; if it doesn't, please point out where it doesn't. Then please compare the categories <genetic algorithms=""> and vice versa. After comparing all the categories. Dease decide which category the paper fits better. and eive a final classification decision.</genetic></case>	CReinforcement Learning>: Papers that discuss learning through trial and error, rewards, penal feedback mechanisms, temporal difference methods, model-based reinforcement learning, learning temporal patients of patients and
please enclose the final decision in <>. Now analyze the information from the given paper:	distances to guide exploration decisions, optimizing exploration have and avgaton costs, using rea- distances to guide exploration decisions, optimizing exploration based on expected benefits and c adapting to dynamic environments, using feedback mechanisms to guide decision-making, coord
Paper information: (Paper Title: Cognitive Computation (Extended Abstract))	ing reactive behaviors, using neural networks as part of a control system, and temporal differ learning, excluding theoretical foundations and proof-based learning, should be categorized as <i forcement Learning&gt;.</i 
(Abstract: Cognitive computation is discussed as a discipline that links together neurobiology, cognitive psychology and artificial intelligence.) (Neighbour Summary:	<rule_learning>: Papers that discuss constructing rules, adapting methods for attribute estima non-myopic learning of regression trees, transforming regression algorithms, ordinal classifica tasks improving learning algorithms, addressing concent overlap problems feature selection or gr</rule_learning>
we papers steen in the ensay nucleus the concept of learning and reasoning, specifically focusing on the Probably Approximately Correct (PAC) learning model and its generalizations. The authors investigate the idea of agnostic learning, where minimal assumptions are made about the target function, and explore the possibilities of this approach through various results and algorithms. The paper also touch on the	algorithms, employing stable models as background knowledge for a top-down ILP learner, impro existing machine learning algorithms, addressing concept overlap, using stochastic complexity form
Learning to Reason framework, which combines learning and reasoning into a single task, and examine the tradeoff between learnability corede strength, and reasoning query range. Overall, the cited papers contribute to the understanding of learning and reasoning in artificial intelligence.)	or employing simulated annealing-oased beam search should be categorized as <rule learning="">. <theory>: Papers that discuss theoretical aspects of learning, implications of findings on lear processes, foundational principles of machine learning, decision trees, ensemble learning, efficience of the second se</theory></rule>
Judgment: The paper titled "Cognitive Computation (Extended Abstract)" discusses the discipling of cognitive computing, which links neurobiology sensitive sensitive and a set of the link of the set	improvements as a primary focus, or practical applications of these theoretical aspects should categorized as <theory>.</theory>
abstract does not explicitly discusses have of the topics mentioned in the Case-Based category, such as case retrieval, adaptation processes, continuous task domains, or case-based reasoning framework. The neighbour summary discusses the Probably Approximately Correct (PAC) hearing model, agnostic	1 will provide the title, abstract, citation summary information of your paper, the categories judge the classification model, and the real categories of the paper, and ask you to verify that the bas judgment for the corresponding categories is accurate.
Iearning, and the Learning to Reason framework, which are more closely related to the Neural Networke category, as they involve learning and reasoning in artificial intelligence. Final decision:	First of all, please compare whether the categories provided by the model and the actual categories in If it matches, you will directly analyze whether you need to add new judgment basis to the correspon- category based on the information and original indement basis of the namer if you need to add it it.
<neural_networks></neural_networks>	you don't need to change anything; if it doesn't match, please analyze why the model may classify paper into the category based on the original judgment basis corresponding to the incorrect cat
one-shot summary LLM CoT we prior Step 80	and then prease summarize the modifications and adjustments to the original judgment bases of the categories, you can choose to remove matches for this paper in the wrong category, add unique featur the true category, or adjust the basis of judgment according to what you think is correct. Describe
Now that you have some descriptions, which will be used as rubrics for the classification task, you need to summarize and refine them for each category to find the best way to express them. Here are the descriptions:	step of the reasoning process in detail, and give the final updated basis of judgment, enclosing the decision in <newpattern></newpattern> . For example:
<case _based="">: If the paper discusses the use of past experiences, memory-based techniques, or case reirieval and adaptation processes to solve new problems, classify it as <case based="">. If the paper discusses the use of past experiences, memory-based techniques, or case retrieval and adaptation</case></case>	Here is a one-shot example; for more details, please refer to the appendix.
processes to solve new problems, classify it as <case based="">. <cenetic algorithms):="" algorithms,="" artificial<br="" discusse="" evolutionary="" genetic="" if="" paper="" processes,="" the="">life, theoretical biology, simulation, evolving neural networks, adapting to changing environments, and principle carbingtion involution exits a feasible mean and environment fragments are sourcements.</cenetic></case>	Paper information: (Papar Title: Compiling Computation (Extended Abstract))
vehicles, and robotics, excluding cost-sensitive classification and robustness of induced models against cost changes, classify it as < Genetic Algorithms>. <neural_networks>: If the paper discusses artificial neural networks, their architecture, training</neural_networks>	(Abstract: Cognitive computation is discussed as a discipline that links together neurobiology, cogn psychology and artificial intelligence. )
methods, applications, connectionist approaches, neurobiology and cognitive psychology links, model calibration, learning parameter values, neural structures and functions, probabilistic methods, genera- tive models, memory-based methods, approximation using radial basis functions, learning from prior knowledse, highly nonlinear models, nattern recommition, stability, and control in nonlinear systems, or	(Reignoour Summary: The papers cited in this essay discuss the concept of learning and reasoning, specifically focusing o Probably Approximately Correct (PAC) learning model and its generalizations. The authors invest
cognitive computation, neurobiology, and cognitive psychology as relevant topics that could be studied using neural networks, classify it as <neural_networks>. <probabilistic_methods>: If the paper discusses Bayesian inference, priors over model parameters, or</probabilistic_methods></neural_networks>	the idea of agnostic learning, where minimal assumptions are made about the target function, and ex- the possibilities of this approach through various results and algorithms. The papers also touch o Learning to Reason framework, which combines learning and reasoning into a single task, and exa
the application of probabilistic Methods to solve practical problems in the context on neutral intervorks, classify it as <probabilistic methods="">. Exclude papers that discuss theoretical aspects of learning, such as cross-validation and its implications. If the paper discusses Bayesian inference, priors over model parameters, or the application of probabilistic methods to solve practical problems in the context</probabilistic>	the tradeoff between learnability, oracle strength, and reasoning query range. Overall, the cited p contribute to the understanding of learning and reasoning in artificial intelligence.) Model judgment category:
of neural networks, classify it as <probabilistic _methods="">. <reinforcement learning="">: Papers that discusse learning through trial and error, rewards, penalties, feedback mechanisms, temporal difference methods, model-based reinforcement learning, learning in trochestic avatems, advantus traditional BL methods, avaloration and naviration costs, using learned</reinforcement></probabilistic>	Neural_Networks Paper True category: Neural_Networks
distances to guide exploration decisions, optimizing exploration based on expected benefits and costs, adapting to dynamic environments, using feedback mechanisms to guide decision-making, coordinat- ing reactive behaviors, using neural networks as part of a control system, and temporal difference	Step-by-Step Analysis:
iearning, excluding theoretical foundations and proof-oased learning, should be categorized as < Aein- forcement _learning>. <rule _learning="">: If the paper discusses constructing rules, adapting methods for attribute estima- tion, non-myopic learning of regression trees, transforming regression algorithms, ordinal classification</rule>	1. **Model Judgment and True Category Comparison** - **Model Judgment Category*: * <pre></pre>
tacks, improving learning algorithms, addressing concept overlap problems, feature selection or greedy algorithms, employing stable models as background knowledge for a top-down ILP learner, improving existing machine learning algorithms, addressing concept overlap, using stochastic complexity formu-	The category -: -< Neural_Networks >- The model has correctly classified this paper under the * <neural_networks>* category. Since bot model's judgment and the true category match, we move on to analyzing whether the original judg</neural_networks>
exclude papers that focus on rule generation and compaction within a broader knowledge discovery and management framework. If the paper discusses constructing rules, adapting methods for attribute estimation, non-myopic learning of regression trees, transforming regression algorithms, ordinal classi-	basis for " <neural_networks>" is accurate or needs to be updated based on this paper's informat 2. **Examination of the Paper Information (Title, Abstract, Neighbour Summary)** . **Paper Title*". *Cognitive Computation (Extended Abstract)*</neural_networks>
Iteration tasks, improving learning algorithms, addressing concept overlap problems, feature selection or greedy algorithms, employing stable models as background knowledge for a top-down ILP learner, improving existing machine learning algorithms, addressing concept overlap, using stochastic complexity formulas, or employing simulated annealing-based heavy source for the latent of the laten	<ul> <li>The title suggests a broad focus on cognitive processes, which could encompass various discip including artificial neural networks.</li> <li>**Abstract**</li> </ul>
<theory>: Papers that discuss theoretical aspects of learning, implications of findings on learning processes, foundational principles of machine learning, decision trees, ensemble learning, efficiency improvements as a primary focus, or practical applications of these theoretical aspects should be</theory>	<ul> <li>The abstract introduces *cognitive computation* as a discipline that links neurobiology, cogn psychology, and artificial intelligence. This broad scope does not directly mention neural network implies a connection to compute the product base.</li> </ul>
categorizen as <theory>. Note: Please ONLY summarize each category without omissions and NOTHING ELSE! And each category is output in the following format:</theory>	<ul> <li>**Noighbour Summary**:</li> <li>The neighbouring papers focus on learning and reasoning, specifically discussing the PAC learning m</li> </ul>
<come_based>&gt; Papers that include [your summary] should be categorized as <come_based>&gt; <genetic_algorithmus>: Papers that include [your summary] should be categorized as <ge- netic_Algorithmus&gt;. <noural networks="">: Papers that include [your summary] should be categorized as <neural networks="">:</neural></noural></ge- </genetic_algorithmus></come_based></come_based>	agnostic learning, and the Learning to Reason framework. While these topics are related to ma learning and artificial intelligence, they do not directly relate to neural networks. 3. **Evaluation of the Existing Judgment Basis for <neural networks="">**</neural>
<probabilistic methods="">: Papers that include [your summary] should be categorized as <probabilistic< td=""><td>The current judgment basis for *<neural_networks>* is as follows: - *If the paper discusses artificial neural networks, their architecture, training methods, applications nectionist approaches, neurobiology and cognitive networkology links. model calibration_learning marks</neural_networks></td></probabilistic<></probabilistic>	The current judgment basis for * <neural_networks>* is as follows: - *If the paper discusses artificial neural networks, their architecture, training methods, applications nectionist approaches, neurobiology and cognitive networkology links. model calibration_learning marks</neural_networks>
"examing" <rel=learning.> Papers that include [your summary] should be categorized as <rule_learning.>. <theory.>: Papers that include [your summary] should be categorized as <theory.>. Please begin with <strat_summary.></strat_summary.></theory.></theory.></rule_learning.></rel=learning.>	values, neural structures and functions, probabilistic methods, generative models, memory-based met approximation using radial basis functions, learning from prior knowledge, highly nonlinear me pattern recognition, stability, and control in nonlinear systems (starting the systems).
<start_summary> Classe Based 5: Papers that discuss the use of past experiences, memory-based techniques, or case retricval and adaptation processes to solve new problems should be extensived as Classe Period's</start_summary>	The paper does not directly fit into this description: - **Artificial neural networks**: The abstract does not mention neural networks explicitly.
<genetic_algorithms>: Papers that discuss genetic algorithms, evolutionary processes, artificial life, theoretical biology, simulation, evolution ary processes, artificial optimization techniques involving genetic algorithms, and applications in machine bearing, autonomous</genetic_algorithms>	<ul> <li>.ceurouology and cognitive psychology inks<sup>-1</sup>: While the paper discusses cognitive computati does not explicitly link this to neural networks or neurobiology.</li> <li>**Determining the Need for Modifications**</li> </ul>
vencese, and robotics should be categorized as <genetic algorithms="">. <neural networks="">: Papers that discuss artificial neural networks, their architecture, training methods, applications, connectionist approaches, neurobiology and cognitive psychology links, model calibration, learning parameter values, neural neurotures and functions, probabilistic methods. enserative models</neural></genetic>	The current judgment basis for * <neural_networks>* is not well-aligned with the content of this paper focuses on cognitive computation and its links to neurobiology and cognitive psychology, does not directly relate to neural networks.</neural_networks>
memory-based methods, approximation using radial basis functions, learning from prior knowledge, highly nonlinear models, pattern recognition, stability, and control in nonlinear systems, or cognitive computation, neurobiology, and cognitive psychology as relevant topics that could be studied using	<ul> <li>**New features need to be added** to the *<neural_networks>* category based on this p specifically to include cognitive computation, neurobiology, and cognitive psychology as relevant t that could be studied using neural networks.</neural_networks></li> </ul>
- etworks are wrong and use categorized as (Neural Networks). - (Probabilistic Methods): Papers that discuss Bayesian inference, priors over model parameters, or the application of probabilistic methods to solve practical problems in the context of neural networks, ex- cluding theoretical appenders of learning such as cross-validation and its implications should be categorized	Updated judgment basis:
as <probabilistic methods="">. <reinforcement learning="">&gt; Papers that discuss learning through trial and error, rewards, penalties, feedback mechanisms, temporal difference methods, model-based reinforcement learning, theraing in technolic avatems, administ radiational BU, methods – methods, model-based reinforcement series of the serie</reinforcement></probabilistic>	<newpattern>Neural_Networks: If the paper discusses artificial neural networks, their architectraining methods, applications, connectionist approaches, neurobiology and cognitive psychology</newpattern>
distances to guide exploration decisions, optimizing exploration and navigation costs, using learned distances to guide exploration decisions, optimizing exploration based on expected benefits and cost, adapting to dynamic environments, using feedback mechanisms to guide decision-making, coordinat- ing reactive behaviors, using neural networks as part of a control system, and temporal difference	mouse cantoration, tearning parameter values, neural structures and functions, probabilistic met generative models, memory-based methods, approximation using radial basis functions, learning prior knowledge, highly nonlinear models, pattern recognition, stability, and control in nonlinear sys
learning, excluding theoretical foundations and proof-based learning should be categorized as <reinforcement learning="">: Papers that discuss constructing rules, adapting methods for attribute estimation, non-avoide learning of preservation theoret transforming methods for attribute estimation, and the statemethod for attribute estimation.</reinforcement>	or cognitive computation, neurobiology, and cognitive psychology as relevant topics that could be st using neural networks, classify it as <neural_networks>.</neural_networks>
tasks, improving learning algorithms, addressing concept overlap problems, fasture selection or greedy algorithms, employing stable models as background knowledge for a top-down ILP learner, improving existing machine learning algorithms, addressing concept overlap, using stochastic complexity formulas,	
or employing simulated annealing-based beam search should be categorized as <rule learning,<br="">&lt;<thory?: aspects="" discuss="" findings="" implications="" learning,="" learning<br="" of="" on="" papers="" that="" theoretical="">processes, foundational principles of machine learning, decision trees, ensemble learning, efficiency immegements as a subject for ensemble and ensemble learning and the second seco</thory?:></rule>	
improvements as a primary rocus, or practical applications of these theoretical aspects should be categorized as <theory>.</theory>	

#### E ONE-SHOT W/ PRIOR SUMMARY + VGRL

#### E.1 ONE-SHOT W/ PRIOR SUMMARY + VGRL STEP 1

The feedback provided by the optimization model suggests that the individual categories of papers have their own unique characteristics. The categorization model performed the judgment of paper categories by using the following features unique to each category of papers as the basis for the judgment: Cone Basel's Paper that include discontinue of pass emperators, meanwr-basel tachslopes, at one vertreini and and particle processors the above segrarshimm shafed for a tapprintees of Cone. Basel's Cleantic, Algorithme,'' Papers that forces on optimization theshipsen impired by evolvitance pro-essors, each as possibilitation-based associated, consouries, and mutation about the comparison of the comparison of the start forward, correstitution, or reservent astronovies, and metric training matched shadood be comparison of the start of the star <Case Based>: If the paper discusses the use of past experiences, memory-based techniques, or case retrieval and adaptation processes to solve new problems, classify it as <Case Based>: <Genetic Algorithms>: If the paper focuses on optimization techniques impired by evolutionary processes, such as population-based search, crossover, and mutation, classify it as <Genetic Algorithms>: Algorithms>: Repare focuses at inficial neural networks, including architectures like feedforward, convolutional, or recurrent networks, and their training methods, classify it as <Neural\_Networks>: - Chernik \_ Detective > Papers that every artificial neural networks, methums preserves as an experimental probability of the paper that drawn which are interpreted in the second neural networks and the second neural networks and the second neural networks and the second neural networks are interpreted in the neural network is an interpreted in the neural network in the neural network in the neural network in the neural network is network in the neural network in the neural network in the neural network is network in the neural network in the neural network is network in the neural network is network in the neural network in the neural network is network in th The Arrange of the second seco often in the <Reinforcement Learning>.
CRule Learning>: If the paper focuses on extracting interpretable decision rules or patterns, often in the form of "if-then" statements, classify it as <Rule Learning>.
<Theory>: If the paper emphasizes theoretical contributions to machine learning or AI, such as mathematical models, complexity theory, or the formal analysis of algorithms, classify it as <Theory>. mathematical models, complexity theory, or the formal analysis of algorithms, classify it as <Theory>. Judge from the information given which category the following easy belongs to. I will provide the title, abstract, citation summary information of your paper, the categories judged by the classification model, and the real categories of the paper, and ank you to verify that the basis of judgment for the corresponding categories is accurate. First of all, please compare whether the categories provided by the model and the actual categories match. If it matches, you will directly makes whether you must be add or thugbene if you need to corresponding you don't need to change anything; if it doen't match, please analyze why the model must be add or thugbene if you need to change anything; if it doen't match, please analyze why the model must classify this paper into the category based on the original judgment haccording to the incorrect category, and then please summarize the basis of judgment in according to what you think is correct. Describe each decision in . e the information from the given paper: e-shot example; for more details, please refer to the appendix. Here is a use-hot example, for more details, places refer to the appendix. Here is a use-hot example, for more details, places refer to the appendix. Here is a use of the second seco Now analyze the given paper: Now analyse the given paper: PAPE Title: Storage and the propositionalization of Non-Determinate Background Knowledge ) (Abstract: It is a welk-known fact that propositional learning algorithms require "good" features to perform well in practice. So a major step in data engineering for inductive learning is the construction of perform well in practice. So a major step in data engineering for inductive learning is the construction of perform well in practice. So a major step in data engineering for inductive learning is the construction of perform well in practice. So a major step in data engineering for inductive learning is the construction of the end of the step in the ste -setures for paper titlet "Learning from positive data" discusses the theoretical and practical aspects of learning from positive examples alone, forexing on the branchility of grammers and logic programs within a proper bound for examples. The seture seture is the strain form positive data with the seture branchility of the seture samples. The alorest and the other papers highlight the importance of learning from positive data, which is a key property of the seture seture terms of the strain form positive data, which is a key aspect of matter data and the data of the seture seture terms of the strain form positive data, which is a key aspect of matter data and the development of new frameworks for learning from noisy data, which is a key aspect of matter data. Final decision: <Genetic\_Algorith Now that you have some descriptions, which will be used as rubrics for the classification task, you need to summarize and refine them for each category to find the best way to express them. Here are the descriptions: to summaries and ordine them for each entropy to find the best way to suppose them. There are the descriptions: Judge from the information given which category the following eacy belong to: Second Secon Rule\_Learning
StephysRep Analysis:
1. "Stoled Judgment and True Category Comparison\*"
•\*\*Model Judgment Category\*: ". "Rule\_Learning>"
•\*\*The Category\*: ". "Rule\_Learning"
•\*\*The Advanced Sategory\*: ". "Rule\_Learning"
•\*\*The Advanced Rule Rule\_Learning"
•\*\*\*Construction of Rule Rule\_Learning"
•\*\*\*Construction of Rule\_Rule\_Learning"
•\*\*\*Construction of Rule Rule\_Learning"
•\*\*\*Const Step-by-Step An module, completity theory or two sectors without emissions and NOTHING ILEEF And each category for expansion the following formatic (Cower Basels / Paper that include (sour emmary) should be categorized as  $< Case_{-}$ factors (the complete the include) (sour emmary) should be categorized as  $< Case_{-}$ antic Algorithms. Chernal Networks: Paper that include (pour emmary) should be categorized as  $< Case_{-}$ factors (the complete the standard for a complete the categorized as  $< Case_{-}$ complete the complete the standard for a complete the categorized as  $< Case_{-}$ complete the complete the standard for a complete the categorized as  $< Case_{-}$ complete the complete the complete the standard for a complete the categorized as  $< Case_{-}$ complete the complete the complete the complete the categorized as  $< Case_{-}$ math Learning). ment\_Learning>. cNule\_Learning>: Papers that include [your summary] should be categorized as <Rule\_Learning>.
cTheory>: Papers that include [your summary] should be categorized as <Theory>.
Please begin with <START\_SUMMARY>. Phase begins with <27ABT\_SIMMARY. OTATAT\_SUMMARY. CarATAT\_SUMMARY.
Const., Agreement and the look of discussions of past experimency, memory-hand technique, or also support to the part of the look of the second se focus on rule construction, propositionalization, and stochastic methods are clearly articulated in the abstract and neighbor summary. •\*No new features need to be added\*\* to the \*<Rule\_Learning>\* category based on this paper, as it fits perfectly within the existing framework. Updated judgment ba <NewPattern>Rule\_Learning: If the paper discusses the construction of rules, propositional-ization, or the use of stochastic methods in the context of inductive learning, classify it as <Rule\_Learning>.</NewPattern> 

## 1026 E.2 ONE-SHOT W/ PRIOR SUMMARY + VGRL STEP 2

one-shot predictor LLM CoT Step 1	one-shot optimizer LLM CoT Step 2
The feedback provided by the optimization model suggests that the individual categories of papers have their own unique characteristics.	The categorization model performed the judgment of paper categories by using the following feat- unique to each category of papers as the basis for the judgment:
Case Based >: If the paper discusses the use of past experiences, memory-based techniques, or case settime.	<case based="">: Papers that include discussions of past experiences, memory-based techniques, or c</case>
<genetic algorithms="">: If the paper focuses on optimization techniques inspired by evolutionary pro- cesses, such as population-based search, crossover, and mutation, classify it as <genetic algorithms="">. <neural networks="">: If the paper covers artificial moved networks including architecture line.</neural></genetic></genetic>	retrieval and adaptation processes to solve new problems should be categorized as <case_based>. <genetic_algorithms>: Papers that focus on optimization techniques inspired by evolutionary p</genetic_algorithms></case_based>
dforward, convolutional, or recurrent networks, and their training methods, classify it as <neu- 1 Networks&gt;- Probabilistic Methods&gt;: If the paper discusses methods that use verbabilistic models to be all set the set of the set</neu- 	<pre>censes, such as population-based search, crossover, and mutation should be categorized as &lt;0 netic_Algorithms&gt;. <neural networks="">: Papers that cover artificial neural networks including architectures like fe</neural></pre>
inty, such as Bayesian networks or hidden Markow models, classify it as <probabilistic maile="" modeus="" to="" un-<br="">inforcement Learning&gt;: If the paper centers on agents learning from interaction with their en- ment through trial and entry main techniques like O learning the second s</probabilistic>	forward, convolutional, or recurrent networks, and their training methods should be categorized <neural networks="">.</neural>
comment that and error, using techniques inte Q-searning or policy gradients, classify it as oreament Learning>. If the paper focuses on extracting interpretable decision rules or patterns, often in mod 56 decision techniques in the classification of the second	<probabilistic _methods="">: Papers that discuss methods using probabilistic models to handle uncertain such as Bayesian networks or hidden Markov models should be categorized as <probabilistic _method<="" p=""></probabilistic></probabilistic>
is form of "ii-then" statements, classify it as <rule _learning="">. Theory&gt;: If the paper emphasizes theoretical contributions to machine learning or AI, such as athematical models, complexity theory, or the formal analysis of algorithms, classify it as <theory>.</theory></rule>	<reinforcement_learning>: Papers that focus on agents learning from interaction with their envir ment through trial and error, using techniques like Q-learning or policy gradients should be categori</reinforcement_learning>
nll provide you with the title, abstract, and citation summary of your paper and ask you to step-by- ap determine if the paper fits into each category. First, please analyze whether the paper matches tegory <case_based>. If it does, please explain how it matches; if it doesn't, please point out where</case_based>	as <keinforcement_learning>. <rule_learning>: Papers that focus on extracting interpretable decision rules or patterns, often in form of large large are all if then? addresses about the extension of a second se</rule_learning></keinforcement_learning>
own't. Then please compare the categories <genetic_algorithms> and vice versa. After comparing the categories, please decide which category the paper fits better, and give a final classification sion, please enclose the final decision in &lt;&gt;&gt;.</genetic_algorithms>	Control togical characteristics of the them statements should be categorized as CRule_Learning >. Cheory>: Papers that emphasize theoretical contributions to machine learning or AI, such as mathem ical models. complexity theory or the formal analysis of algorithms, or discuss ontimality, dominat.
ge from the information given which category the following essay belongs to. Ill provide you with the title, abstract, and citation summary of your paper and ask you to step-by-step	and bounded convergence rates in the context of repeated games should be categorized as < Theory
ermine if the paper fits into each category. First, please analyze whether the paper matches category ass_Based>. If it does, please explain how it matches; if it doesn't, please point out where it doesn't. en please compare the categories <genetic_algorithms> and vice versa. After comparing all the</genetic_algorithms>	Judge from the information given which category the following essay belongs to. I will provide the title, abstract, citation summary information of your paper, the categories judge
egories, please decide which category the paper fits better, and give a final classification decision, we enclose the final decision in $<>$ . v analyze the information from the given paper:	the classification model, and the real categories of the paper, and ask you to verify that the bas judgment for the corresponding categories is accurate.
re is a one-shot example; for more details, please refer to the appendix.	If it matches, you will directly analyze whether you need to add new judgment basis to the correspon category based on the information and original judgment basis of the paper, if you need to add it, if
uper information: aper Title: Stochastic Propositionalization of Non-Determinate Background Knowledge ) heteroit is a well because fast that approximatel because a lamither approximation of the store in the store of the store	you don't need to change anything; if it doesn't match, please analyze why the model may classify paper into the category based on the original judgment basis corresponding to the incorrect cate
form well in practice. So a major step in data engineering for inductive learning is the construction of sod features by domain experts. These features often represent properties of structured objects, where	and then please summarize the modifications and adjustments to the original judgment bases of the categories, you can choose to remove matches for this paper in the wrong category, add unique featur
supersy synamy is the occurrence or a certain substructure having certain properties. To partly tomate the process of "feature engineering", we devised an algorithm that searches for features which defined by such substructures. The algorithm stochastically conducts a top-down search for first-order	the true category, or adjust the basis of judgment according to what you think is correct. Describe step of the reasoning process in detail, and give the final updated basis of judgment, enclosing the
ases, where each clause represents a binary feature. It differs from existing algorithms in that its search not class-blind, and that it is capable of considering clauses ("context") of almost arbitrary length e). Preliminary experiments are favorable, and support the view that this approach is promisive )	decision in <newpattern></newpattern> . For example:
sighbour Summary: s papers cited in this essay discuss various techniques and approaches in the field of Rule Learn- s ancefically in Inductive Looie Personaming (ILP). The field of Rule Learn-	Here is a one-shot example; for more details, please refer to the appendix.
g, spectromany in inductive Logic Frogramming (LFF). The first paper re-appraises the development (techniques for inverting deduction and introduces Mode-Directed Inverse Entailment (MDIE) as a neralisation and enhancement of previous approaches. The second paper proposes an extension of	Now analyze the given paper:
as teature-vector representation to allow the value of a feature to be a set of strings, which can be Hiciently and naturally represented in real-world learning problems. The third paper describes a system amed SFOLL that uses a stochastic search method to alleviate the local optimization problem in greedy	(Paper Title: Learning from positive data ) (Abstract: Gold chowed in 1967 that not are service service service in the second service in the second service se
lgorithms. Overall, these papers highlight the importance of efficient and effective techniques in Rule earning and ILP.)	(ADMIARCE: GOID SHOWED IN 1997) that not even regular grammars can be exactly identified from pos examples alone. Since it is known that children learn natural grammars almost exclusively from posi- examples. Gold's result has been used as a theoretical uncertified from block of the second secon
Judgment: In paper titled "Stochastic Propositionalization of Non Determinent Problemson Knowledge" 1	compace, Goid's result has been used as a theoretical support for Chomsky's theory of innate hit linguistic abilities. In this paper new results are presented which show that within a Bayesian frame not only grammars, but also logic programs are lawnship with achieve law avancted over for
experiment of the second secon	examples only. In addition, we show that the upper bound for expected error of a learner which maxin the Bayes' posterior probability when learning from mostive examples is within a small additive term of
represents a onary teature. This approach is different from existing algorithms in that its search is not class-blind and can consider clauses of almost arbitrary length. The abstract and the cited papers highlight the importance of feature engineering and the use of stochastic	which does the same from a mixture of positive and negative examples. An Inductive Logic Program implementation is described which avoids the pitfalls of greedy search by global optimisation of
earch methods to alleviate local optimization problems, both of which are central concepts to Rule earning and ILP. The neighbour summary further supports the categorization. discussing the development of techniques for	function during the local construction of individual clauses of the hypothesis. Results of testing implementation on artificially-generated data-sets are reported. These results are in agreement with
nductive logic programming and the importance of efficient and effective methods in rule learning.	theoretical predictions. ) (Neighbour Summary:
<pre>cRule_Learning&gt;</pre>	The papers cited in this essay discuss the limitations of current inductive logic programming sys in handling noise and learning recursive predicates. A new framework for learning from noisy data
no dist summers 111/ C-T Store 2	fixed example size is presented, which incorporates a Bayesian heuristic for finding the most proh hypothesis. This approach is implemented in an ILP system called Lime, which is shown to handle a
and summary first cost one -	better than other systems like FOIL and PROGOL, and is capable of learning from only positiv negative data.
w that you have some descriptions, which will be used as rubrics for the classification task, you need summarize and refine them for each category to find the best way to express them. re are the descriptions:	Common points that reflect the category of this paper include: - Handling noise in inductive logic programming systems I common possible to a solution of the solution of th
lge from the information given which category the following essay belongs to.: ase _Based>: If the paper discusses the use of past experiences, memory-based techniques, or	Dearling recursive predicates     Improving the performance of ILP systems     Dearloging new frameworks for learning from poiss data ) Model indement category:
se retrieval and adaptation processes to solve new problems, classify it as <case_based>. If the per discusses the use of past experiences, memory-based techniques, or case retrieval and adaptation presses to solve new problems, classify it as <case_based>.</case_based></case_based>	Genetic_Algorithms Paper true category:
Genetic Algorithms>: If the paper focuses on optimization techniques inspired by evolutionary pro-	Theory
nees, such as population-based search, crossover, and mutation, classify it as <_veneticAgorithms>. Neural_Networks>: Papers that cover artificial neural networks, including architectures like feed- srward, convolutional, or recurrent networks, and their training methods should be categorized as	Step-by-Step Analysis:
Neural Networks>. Probabilistic Methods>: If the paper discusses methods using probabilistic models to handle uncer- inty, such as Baywsian networks or hidden Markov models, classify it as <probabilistic methods="">.</probabilistic>	<ol> <li>**Model Judgment and True Category Comparison**         <ul> <li>**Model Judgment Category**: *<genetic_algorithms>*</genetic_algorithms></li> </ul> </li> </ol>
<reinforcement learning="">: Papers that focus on agents learning from interaction with their environ- ment through trial and error, using techniques like Q-learning or policy gradients should be categorized as &lt; Reinforcement Learning&gt;</reinforcement>	The model has incorrectly classified this paper under the * <genetic_algorithms>* category. Since</genetic_algorithms>
<rule learning="">: Papers that focus on extracting interpretable decision rules or patterns, often in the form of logical clauses or "if-then" statements should be categorized as <rule learning="">. C'heory&gt;: If the paper emphasize theoretical contributions to machine learning or AL such as</rule></rule>	classified this paper into the incorrect category and make necessary adjustments to the judgment b 2. **Examination of the Paper Information (Title Abstract Neighbour Summary)**
mathematical models, complexity theory, or the formal analysis of algorithms, or discusses optimality, domination, and bounded convergence rates in the context of repeated games, classify it as <theory>. If the means methods are domential analysis to method be presented as the second seco</theory>	<ul> <li>**Paper Title**: *Learning from positive data*</li> <li>The title suggests a focus on learning from positive data, which is more aligned with theoretical aspects and the suggest of the</li></ul>
If the paper emphasizes theoretical controlutions to machine learning or AI, such as mathematical models, complexity theory, or the formal analysis of algorithms, or discusses optimality, domination, and bounded convergence rates in the context of repeated games, classify it as <theory>. Additionally,</theory>	of machine learning rather than genetic algorithms **Abstract**:
consider papers that analyze the bias and complexity of learning algorithms, propose new mathematical models for learning, or explore the efficiency and scalability of machine learning methods. If the paper emphasizes theoretical contributions to machine learning or AI, such as mathematical models,	<ul> <li>The abstract discusses the learnability of logic programs and grammars from positive examples we a Bayesian framework. It also presents results on the upper bound for expected error of a learner</li> </ul>
complexity theory, or the formal analysis of algorithms, or discusses optimality, domination, and bounded convergence rates in the context of repeated games, classify it as <theory>. If the paper emphasizes theoretical contributions to machine learning or AI, such as mathematical models complexity theory</theory>	describes an implementation in Inductive Logic Programming (ILP). These topics are more aligned theoretical aspects of machine learning and ILP rather than genetic algorithms.
or the formal analysis of algorithms, or discusses optimality, domination, and bounded convergence rates in the context of repeated games, classify it as <theory additionally,="" discusses<br="" if="" paper="" the="">theoretical models of hearing bounds on error rates and the demonstrates of difference of the second second</theory>	<ul> <li>"Neighbour Summary":</li> <li>The neighbouring papers focus on the limitations of current ILP systems, the development of formation of the large large form pairs data and the second second</li></ul>
chassify it as <theory.>. If the paper discusses theoretical contributions to machine learning or AI, such as mathematical models, complexity theory, or the formal analysis of algorithms, or discusses such as mathematical models.</theory.>	reauceworks for learning from noisy data, and improving the performance of ILP systems. These to are also more aligned with theoretical aspects of machine learning and ILP. 3. **Evaluation of the Evisting Judgment Basis for <constitute algorithme="">**</constitute>
opumany, wommation, and nonnees convergence rates in the context of repeated games, or focuses on the learnability of concepts and the development of new learning techniques, classify it as <theory>. If the paper emphasizes theoretical contributions to machine learning or AI, such as mathematical</theory>	The current judgment basis for * <genetic_algorithms>* is as follows:</genetic_algorithms>
models, complexity theory, or the formal analysis of algorithms, or discusses optimality, domination, and bounded convergence rates in the context of repeated games, classify it as <theory>.</theory>	based search, crossover, and mutation, classify it as <genetic_algorithms>.* The paper does not fit this description:</genetic_algorithms>
Note: Please ONLY summarize each category without omissions and NOTHING ELSE! And each category is output in the following format: "Case, Based-2: Paners that include loops remembered hearth hearth and the second	<ul> <li>**Evolutionary processes**: The paper discusses learning from positive data within a Bayesian frame and the implementation of an ILP system, which does not involve evolutionary processes</li> </ul>
Genetic Algorithms>: Papers that include [your summary] should be categorized as <case_dawed>. etc. Algorithms&gt;: Papers that include [your summary] should be categorized as <ge- etic Algorithms&gt;.</ge- </case_dawed>	<ol> <li>**Evaluation of the Existing Judgment Basis for <theory>** The current judgment basis for *<theory>* is as follows:</theory></theory></li> </ol>
.veura: vetworze>: Paperz that include [your summary] should be categorized as <neural_networke>. (Probabilistic_Methods&gt;: Papers that include [your summary] should be categorized as <probabilis- ic_Methods&gt;.</probabilis- </neural_networke>	<ul> <li>*If the paper emphasizes theoretical contributions to machine learning or AI, such as mathema models, complexity theory, or the formal analysis of algorithms, or discusses optimality. domination</li> </ul>
Reinforcement Learning>: Papers that include [your summary] should be categorized as <reinforce- ent Learning&gt;. Rule Learning&gt;: Papers that include [your summary] should be categorized as <rule learning=""></rule></reinforce- 	bounded convergence rates in the context of repeated games, classify it as <theory>.* The pape this description well:</theory>
Theory>: Papers that include [your summary] should be categorized as <theory>. Please begin with <start_summary></start_summary></theory>	<ul> <li>**Theoretical contributions**: The paper presents new results on the learnability of logic programs grammars from positive examples within a Bayesian framework, which is a theoretical contribution</li> </ul>
START SUMMARY> Case Based>: Papers that discuss the use of past experiences, memory-based techniques, or case	machine learning. - **Mathematical models**: The paper uses a Bayesian framework, which is a mathematical model.
retrieval and adaptation processes to solve new problems should be categorized as <case based="">. <genetic_algorithma>: Papers that focus on optimization techniques inspired by evolutionary pro- cesses, such as population-based search, crossover, and mutation should be categorized as <ge-< td=""><td>learning from positive data. ***Formal analysis of algorithms**: The paper discusses the upper bound for expected error of a lea</td></ge-<></genetic_algorithma></case>	learning from positive data. ***Formal analysis of algorithms**: The paper discusses the upper bound for expected error of a lea
netic_Algorithms>: Neural_Networks>: Papers that cover artificial neural networks, including architectures like feed- orward.convolutional, or recurrent networks, and their training methods should be returned and the statement of the stateme	which involves a formal analysis of an algorithm. 5. **Determining the Need for Modifications**
Neural Networks>. Probabilistic Methods>: Papers that discuss methods using probabilistic models to handle uncertainty,	The current judgment basis for " <theory>" is well-aligned with the content of this paper. The focu- theoretical contributions, mathematical models, and formal analysis of algorithms are clearly articul</theory>
ucn as nayeenan networks or hidden Markov models should be categorized as <probabilistic methods="">. (Reinforcement Learning): Papers that focus on agents learning from interaction with their environ- ment through trial and error, using techniques like Q-learning or policy gradients should be categorized</probabilistic>	in the abstract and neighbor summary. - **Remove the match for this paper in the wrong category <genetic_algorithms>** and add un features in the true category *<theory.>*</theory.></genetic_algorithms>
ss <reinforcement learning="">. Rule_Learning&gt;: Papers that focus on extracting interpretable decision rules or patterns, often in the form of logical clauses or "lithen" statements should be extensived as <rule_learning".< td=""><td>Updated judgment basis:</td></rule_learning".<></reinforcement>	Updated judgment basis:
<theory.): ai,="" as="" contributions="" emphasize="" learning="" machine="" mathe-<br="" or="" papers="" such="" that="" theoretical="" to="">matical models, complexity theory, or the formal analysis of algorithms, or discuss topics like optimality,</theory.):>	<newpattern>Genetic Algorithms: If the paper focuses on optimization techniques inspired by</newpattern>
summanum, sounded convergence rates, mas, complexity, or the development of efficient algorithms should be categorized as <theory>. <end_summary></end_summary></theory>	lutionary processes, such as population-based search, crossover, and mutation, classify it as netic_Algorithms>.
	<newpattern>Theory: If the paper emphasizes theoretical contributions to machine learning or such as mathematical models, complexity theory, or the formal analysis of algorithms, or discu</newpattern>
	optimality, domination, and bounded convergence rates in the context of repeated games, classify <theory>.</theory>

E.3 ONE-SHOT W/ PRIOR SUMMARY + VGRL STEP 80

#### The categorization model performed the judgment of paper categories by using the following features using to category of papers at the basis for the judgment: Case Langory 1: Papers that discuss the use of past caprelences, memory-hared techniques, case retrieval domains should be categorized as <Case Based>. Constri Apportants: Papers that discuss the use of past caprelences, memory-hared techniques, case retrieval domains should be categorized as <Case Based>. Constri Apportants: Papers that include applications of achieves caprelences, memory-hared techniques, case retrieval techniques in continuous take domains should be categorized as <Case Based>. Constri Apportants: Papers that include applications of genetic algorithms for evolutionary forces, mate preferences, learning-should be categorized at <Cose of genetic algorithms). <</td> <Nural Networks>? Papers that discuss neural network concepts, applications, calibration, divide prototype styles of generalization, massively parallel architecture, approximation problem, protoballistic decision-making, confidence measures, pruning methods, stability and control in nonlinear systems, or partical applications. <Probabilistic Methods>: Papers that include discussions of stochastic processes, estimation with incomplete data, martingale theory, litidel Markov Models, stability and control in nonlinear systems, or plotabilistic methods to neural networks and graphical models, and the application of probabilistic methods to neural networks and graphical medical, and though theory, include markov models, and the application of probabilistic methods to neural networks and graphical medics, and the application of probabilistic methods to neural networks and graphical medics, and the application of probabilistic methods to neural networks and graphical models, and the application of probabilist The categorization model performed the judgment of paper categories by using the following features unique to each category of papers as the basis for the judgment: The feedback provided by the optimization model suggests that the individual categories of papers have their own unique characteristics. From things the theorem terms. The methods are associated with the second seco Benchmark and Stranding and Stranding Stran Including factor graphs Jadge from the information given which category the following essay belongs to. I will provide the titls, abstract, citation nummary information of your paper, the categories judged by the titls, abstract, distance, and the second sec Paper advances: Paper advances: (Paper Title: Cognitive Computation (Extended Alstracti)) (Paper Title: Cognitive Computation (Extended Alstracti)) (Paper Title: Cognitive Computation (Extended Alstracti)) (Paper Title: Cognitive Computation (Extended Alstraction)) (Paper Title: Cognitive Computation)) (Paper Title: Cognitive Computation) (Paper Title: Cognitive Computation)) (Paper Title: Cognitiv Judgmont The paper titled "Cognitive Computation (Extended Abstract)" discusses the discipline of cognitive computation, which links neurobiology, cognitive psychology, and artificial intelligence. However, the abstract does not explicitly discuss any of the topic mentioned in the Cane-Band category, such as case retrieval, adaptation processes, or practical applications of machine learning techniques in continuous domains. neighbour summary discusses the Probably Approximately Correct (PAC) learning model, agnostic ing, and the Learning to Reason framework, which are more closely related to the Probabilistic ods category, as they involve probabilistic reasoning and learning. For example: Here is a one-shot example; for more details, please refer to the appendix. Now analyze the given paper: Paper information: (Paper Title: Cognitive Computation in discussed as a discipline that links together neurobiology, cognitive paychology and artificial intelligence. ) (Neighbour Summary: psychology and artificial intelligence.) (Neighbour Summary: psychology and artificial intelligence.) (Neighbour Summary: the idea of agnostic learning, where minimal assumptions are made about the target function, and explore the possibilities of this approach through various results and digorithms. The authors introdue on the Learning to Reason framework, which combines learning and reasoning into a single task, and examine the tradeoff between learnability oracle strength, and reasoning query range. Overall, the cited papers Model judgmont category: Model judgmont category: r that you have some descriptions, which will be used as rubrics for the classification task, you need annuarize and refine them for each category to find the best way to express them. are the description How are the descriptions: Alogs from the theorem taking each schedury the following eacy belongs to: Ling from the theorem taking each schedury the following eacy belongs to: the schedure of the schedure each schedure each schedure each schedure each provide the schedure each schedure schedure each schedure each schedure each schedure each schedure each schedure schedure each schedure each schedure each schedure each schedure each schedure schedure each schedure each schedure each schedure each schedure each schedure each schedure schedure each schedure each schedure each schedure each schedure each schedure each schedure data each schedure e Paper true ca Neural Netw image and a second s <Genetic\_Algorith processes, adaptati evolutionary forces behaviors in unders <Neural\_Networks relations of generation in the performance is a strategistic priority on a the inter of generation in the strategistic priority of the strategistic priority o Step-by-Step Analys \*\*Model Judgment Category\*\*: \*<Probabilistic \_Methods>\* \*\*True Category\*\*: \*<Neural Network>>\* The model has incorrectly classified this paper under the \*<Probabilistic Methods>\* category. We need to analyze why the model made this classification and adjust the judgment basis accordingly. 2. \*\*Examination of the Paper Information (Tite, Abstract, Neighbour Summary)\*\* \*\*Paper Title\*: \*Cognitive Computation (Extended Abstract)\* The title suggests a brack focus on cognitive processes, which could encompass various disciplines including "Neural Network\*. \* \*Abstract\*\* including "Neural\_Networks". "Abstract discusse "applicit computations" as a discipline linking sensohiology, cognitive psychology. The abstract discusses "applicit computations" as a discipline linking sensohiology, cognitive psychology. "The abstract discusses application of the sensor directly meeting. "Neural\_Networks", the byoad scope of cognitive computation could include neural networks as a method or tool within artificial intelligence. "Neighbour Summary": "The neighbouring papers focus on "PACI energing," agnostic learning", and the "Learning to Reason" framework. These topics are more aligned with "Probabilistic Methods" than "Neural\_Networks", as "Technication of the Existing Judgment Basis for <Probabilistic Methods." If the paper includes discussions of stochastic processes, existing and the "Learning article theory. "If the paper includes discussions of stochastic processes, existing and the structure, including factors graphs and being formation, application of probabilistic methods to neural networks, classify it as <Probabilistic Methods." The paper does not fit this discriptions will: "The paper does not fit this discriptions will. ""Strukturks Methods". The abstract does not discuss martingle theory. ""Stindiand haker Models". The abstract does not mention stochastic processes. ""Standards Web Models." The abstract does not discuss more aliacus or probabilistic inference and ""Strukturks Models". The abstract does not mention stochastic processes. ""Stindiand haker Models". The abstract does not discuss probabilistic inference and ""Stindiand theory". The abstract does not discuss probabilistic inference and ""Stindiand theory". The abstract does not mention stochastic processes. ""Stindiand haker Models". The abstract does not mention stochastic processes. ""Stindiand theory". The abstract does not discuss probabilistic inference and ""Stindiand theory Models." The abstract does not mention stochastic processes. ""Stindiand theory Models." The abstract does not mention stochastic becory. Note: Press ONLY summarize and category without omissions and NOTHING ELSE! And each category is to indicate for the strength in the following format that include jour summary labolad be categorized as <Case\_Based>: <Genetic\_Algorithms): Appear that include [your summary] abould be categorized as <Ge =\_Ilaced>: Papers that include [your summary] should be categorized as <Case\_Ilased>. stdt\_Agorithms): Papers that include [your summary] should be categorized as <Ger-ral\_Metworks>: Papers that include [your summary] should be categorized as <Neural, Networks>. Sublistic\_Methods): Papers that include [your summary] should be categorized as <Neural, Networks>. \*\*Probabilistic inference and optimization\*\*: The abstract does not discuss probabilistic inference and optimization. \*\*Probabilistic from social choice theory\*: \*\*Probabilistic methods in rational representation and belief formation. \*\*Probabilistic methods in rational representation and belief formation. \*\*Application of probabilistic methods in coding theory\*: The abstract does not mention factor graphs or graphical models\*: The abstract does not discuss the application of probabilistic methods in coding theory\*: The abstract does not discuss the application of probabilistic methods in coding theory\*: The abstract does not discuss the application of probabilistic methods in coding theory. Learning>: Papers that include [your summary] should be categorized as <Reinford ment\_Learning>: chuie\_Learning>: Papers that include [your summary] should be categorized as <Rule\_Learning>: cTheory>: Papers that include [your summary] should be categorized as <Theory>. Alberge Lemma, F. Paper that header header head in categories of the startic stress of the startic stress of the startic stress of the startic stress of the • "Asoling graphs and graphical models": The abstract does not mention factor graphs or graphical • "Application of probabilistic methods to neural networks": The abstract does not discuss the applica-tion of probabilistic methods to neural networks. • "Determining the Need for Modifications": The abstract does not discuss any of the topics listed in the judgment basis. • "Remove matches for this paper in the wrong category": The paper should not be classified under • "Probabilistic Methods." • "Add under scatters on this consequent". The paper should be classified under \* Chousil and the statement • "Add under scatters on this consequent". The paper should be classified under \* chouse a set of the • "Add under scatters on this consequent". The paper should be classified under \* chouse a set of the • "Add under scatters on this consequent". The paper should be classified under \* chouse a set of the • "Add under scatters on this consequent". The paper should be classified under \* chouse a set of the • "Add under scatters on this consequence in the consequence of the set of the • "Add the basis of judgment\*: The judgment basis for \* cProbabilistic Methods." \* and • adjusted to exclude papers that discuss cognitive computation or artificial intelligence broadly, as these topics may not necessarily involve probabilistic methods. Updated judgment basis: /> VevPatters>Probabilistic Methods: If the paper includes discussions of stochastic processes, estimation with incomplete data, martingale theory, Hidden Markow Models, probabilistic inference and optimization as function of problem structure, formal results from social choice theory, deniat reasoning, probabilistic theory, including factor graphs and graphical models, and the application of probabilistic metrods, classify it as c. Probabilistic Wethods. Theorem, exclude papers that discuss cognitive computation or artificial intelligence broadly, as these topics may not necessarily involve probabilistic methods.../NewPattern>

# <sup>1134</sup> F ZERO-SHOT W/O PRIOR SUMMARY + VGRL

#### 1136 F.1 ZERO-SHOT W/O PRIOR SUMMARY + VGRL STEP 1 1137

1138		zero-shot optimizer LLM CoT wo prior Step 1
1139		Ontimination Step
1140	zero-shot predictor LLM CoT we prior Step 1	Optimization Step Your goal is to learn the best descriptions for the model. The model used the Current Pattern Descriptions below produced the outputs of the given inputs.
1141	Inference Step You will use the descriptions below to predict the output of the given information about a paper including: title, abstract and a summary of information about the papers cited in this paper. You need to tell me tables of the followine summary of information about the papers cited in this paper. You need to tell me	** Current Pattern Descriptions: ** Please refer to the following judgement criteria to determine which category the following paper belongs
1142	<case based="">, <genetic algorithma="">, <neural networks="">, <probabilistic_methods>, <reinforce- neent Learning&gt;, <theory> Here is the pattern descriptions and the information about the paper: Here is the pattern descriptions and the information about the paper:</theory></reinforce- </probabilistic_methods></neural></genetic></case>	Judge from the information given which category the following essay belongs to. You are provided with the characteristics of a node, another model's judgment of its category, and its
1143	You will use the descriptions below. Judge from the information given which category the following essay belongs to. ** Input: **	true category. Please optimize the Pattern Descriptions for better prediction. ** Inputs (a paper): **
1144	(raper little Stochastic Propositionalization or Non-Determinate Background Klowwings ) (Abstract: It is a well-known fact that propositional learning algorithms require "good" features to perform well in practice. So a major step in data engineering for inductive learning is the construction of good features by domain experts. These features often represent properties of structured objects, where	(Paper Title: Stochastic Propositionalization of Non-Determinate Background Knowledge) (Abstract: It is a well-known fact that propositional learning algorithms require "good" features to perform well in practice. So a major step in data enzineering for inductive learning is the construction of
1145	a property typically is the occurrence of a certain substructure having certain properties. To partly automate the process of "feature engineering", we deviaed an algorithm that searches for features which are defined by such substructures. The algorithm stochastically conducts a top-down search for first-order clauses, where each clause represents a binary feature. It differs from existing algorithms in that its search	good features by domain experts. These features often represent properties of structured objects, where a property typically is the occurrence of a certain substructure having certain properties. To partly
1146	is not class-blind, and that it is capable of considering clauses ("context") of almost arbitrary length (size). Preliminary separiments are favorable, and support the view that this approach is promising.) (Neighbour Summary: The paper cited in this easy discuss various techniques and approaches in the field of Rule Learn-	automate the process of "feature engineering", we devised an algorithm that searches for features which are defined by such substructures. The algorithm stochastically conducts a top-down search for first-order algorithm of the stochastic stochastical of the stochastic stoch
1147	ing, specifically in Inductive Logic Programming (ILP). The first paper re-appraises the development of techniques for inverting deduction and introduces Mode-Directed Inverse Entailment (MDIE) as a generalization and enhancement of previous approaches. The second paper proposes an extension of the feature-vector representation to allow the value of a feature to be a set of strings, which can be	is not class-blind, and that it is capable of considering clauses ("context") of almost arbitrary length (size). Preliminary experiments are favorable, and support the view that this approach is promising.)
1148	efficiently and naturally represented in real-world learning problems. The third paper describes a system named SPOIL that uses a stochastic search method to alleviate the local optimization problem in greedy algorithms. Overall, these papers highlight the importance of efficient and effective techniques in Rule Learning and ILP.)	(Neighbour Summary: The papers cited in this essay discuss various techniques and approaches in the field of Rule Learn-
1149	** Output Format: ** Please give your output strictly in the following format: Evaluations: Your stendowsten analyzes and results	ing, specifically in inductive Logic Programming (ILP). The first paper re-appraises the development of techniques for inverting deduction and introduces Mode-Directed Inverse Entailment (MDIE) as a generalisation and enhancement of previous approaches. The second paper proposes an extension of
1150	Output: [Pick one in ( <case based="">, <genetic_algorithms>, <neural_networks>, <probabilistic_methods>, <reinforcement_learning>, <rule_learning>, <theory>)], e.g. <case_based> u</case_based></theory></rule_learning></reinforcement_learning></probabilistic_methods></neural_networks></genetic_algorithms></case>	the feature-vector representation to allow the value of a feature to be a set of strings, which can be efficiently and naturally represented in real-world learning problems. The third paper describes a system
1151	Please ONLY reply according to this format. Do not include any other words or step-by-step breakdowns. Now take a deep breakh and provide a concise explanation and output.assistant Perulamentions: The angue discusses the stechastic propositionalization of non-determinate background	named SFOIL that uses a stochastic search method to alleviate the local optimization problem in greedy algorithms. Overall, these papers highlight the importance of efficient and effective techniques in Rule Learning and ILP.)
1152	toppintnesses, the jupilet intrastance we receive any population introduce in the state of the s	** The model outputs: ** Rule_Learning
1153	the locus on Rule Learning suggest that the paper belongs to the <rule_learning> category. Output: <rule_learning></rule_learning></rule_learning>	** The target outputs: ** Rule Learning If the model cutout differe from the target output, undate the descriptions for both the model's output
1154	zero-shot summary LLM CoT wo prior Step 1	ategory and the target output category to reduce classification error on both current and future data. If the model and target outputs are the same, update the description for this category only. Limit your
1155	Now that you have some descriptions, which will be used as rubrice for the classification task, you need to summarize and refine them for each category to find the best way to express them. Here are the descriptions:	'New Pattern Descriptions' to less than 150 words per category. Think step by step provide your output strictly in the following format:
1156	<case based="">: The papers that describe the application of memory-based techniques, caue-based reasoning, or design systems in various domains, including structural design of buildings, should be categorized as <case based="">. The papers that discuss goal-driven learning, introspection, and the importance of availabation in artificial intelligence, matignals those that generating from</case></case>	** Output Format: ** Please think step by step and give your outputs strictly in the following format:
1157	specific cases and experiences, should be categorized as <case. based="">. <genetic, algorithm="">: The papers that focus on generic is algorithms for solving large-scale optimization problems, improving solution quality, and exploring the effectiveness of various crossover operators should be categorized as <genetic algorithm="">.</genetic></genetic,></case.>	Reasoning: [Provide a concise summary of the reasoning process, focusing on the key insights that lead to the
1158	< Neural_Networks>: The papers with a focus on neural networks, their applications, and theoretical perspectives should be categorized as < Neural_Networks>. The papers that discuss pruning methods for neural networks, including the adaptation of pruning strength to the evolution of weights and loss of semeralization during training whould be extensioned as < C Merrar Networks>.	hnal decision. Avoid listing multiple steps. Ensure the reasoning is clear and justifies the new pattern descriptions.] New Pattern Descriptions:
1150	Kainforcement Learning>: The papers with a focus on learning, adaptation, and efficient algorithms for playing game against unknown adversaries should be categorized as <reinforcement learning="">. <rule learning="">: The paper that discuss techniques and approaches in Inductive Logic Programming (IIP): use's assertion for features defined be subjecture used.</rule></reinforcement>	[Please insert your new descriptions here. The new descriptions MUST BE DIRECTLY based on the key features and insights identified in the input paper. Update the descriptions ONLY for the categories where
1160	length, should be categorized as <role_learning>. <theory>: The papers that focus on general theories and principles of artificial intelligence, without specific emphasis on goal-driven learning or explanation, should be categorized as <theory>. The</theory></theory></role_learning>	the model output differs from the target output, or if they match, update ONLY that category. Ensure that only the following categories are used: <case_based>, <genetic_algorithms>, <neural_networks>, <prohabilistic_mathods> <reinforcement_lasruing> <rule_lasruing> <theory. each="" td="" undated<=""></theory.></rule_lasruing></reinforcement_lasruing></prohabilistic_mathods></neural_networks></genetic_algorithms></case_based>
1161	papera wvin a nocia bu interventia concepts, maximizati a manyata, intro compractionar obtaness na game theory should be categorized as <a cheorys.="" discuss="" game="" introduce="" new<br="" papera="" that="" the="" theory,="">classes of adversaries, and provide efficient algorithms for learning to play games against computationally bounded adversaries should be categorized as <a a="" cheorys.<=""></a></a>	description MUST BE enclosed within <newpatters descriptions="" for<br="" include="" newpatters="" only="" tags.="">the categories being updated. If the model output and target output are the same, update ONLY that</newpatters>
1160	Note: Please ORLY summarize each category without omissions and NOTHING ELSE! And each category is output in the following format: <come_tamed>: Poper that include [your summary] should be categorized as <come_tamed>: <come_tamed>: Come_Tamed&gt;:</come_tamed></come_tamed></come_tamed>	category and NO OTHERS.] For example: NewPotternCaseBased>: The papers with [your new pattern description] should be categorized as
1162	Connette Algorithmas: Papers that include [your summary] should be categorized as <generatic algorithmas.<="" p=""> Anural Networks): Papers that include [your summary] should be categorized as <neural networks).<="" p=""> CProbabilistic_Methods): Papers that include [your summary] should be categorized as <probabilities.< p=""></probabilities.<></neural></generatic>	<case_based.< (your="" <case_based.<="" as="" be="" case_ased.="" case_ased.<="" categorized="" description)="" new="" papers="" partern="" should="" td="" the="" with=""></case_based.<>
1103	Comparison of the second se	rized as <genetic_algorithms>.</genetic_algorithms>
1104	< 1 neery>: raper/ that include [your summary shound be categorizen as < 1 neery>. Please begin with < START_SUMMARY> <start_summary></start_summary>	target output are the same, update ONLY that category and NO OTHERS. Now take a deep breath and provide a concise and logical Reasoning and New Pattern Descriptions.assistant
C011	Conset index2, : a pirct interface interfac	Reasoning: The paper discusses the stochastic propositionalization of non-determinate background knowledge, which
1100	pronema, improving solution quarity, and exporting crossover operators. CNeural Networks: Papers that focus on neural networks, their applications, and theoretical perspectives, including pruning methods for neural networks. CProbabilistic Methods: No description available.	is a technique used in Inductive Logic Programming (ILP). The algorithm searches for features defined by substructures, and it is capable of considering (aluese of almost arbitrary length. The papers cited
1107	<antimoreamentlearning.>: Papter that incurs on tearning, anaptation, and emcent algorithms for playing games against unknown adversaries. <rule _learning.="">: Papters that discuss techniques and approaches in Inductive Logic Programming (ILP), such as searching for feature defined by substructures and considering clauses of almost arbitrary</rule></antimoreamentlearning.>	in the neighbour summary discuss various techniques and approaches in the field of Rule Learning, specifically in ILP. The key insight is that the paper is related to Rule Learning, and the neighbour
1108	iength. <thory>: Papers that focus on general theories and principles of artificial intelligence, theoretical concepts, mathematical analysis, and computational boundedness in game theory, or discuss game theory, introduce new classes of adversaries, and provide efficient algorithms for learning to play games</thory>	output are the same, which means we only need to update the description for the Rule_Learning category.
1169	against computationally bounded adversaries.	New Pattern Descriptions: <newpattern><rule learning="">: The papers that discuss techniques and approaches in Inductive</rule></newpattern>
1170		Logic Programming (LLP), such as searching for features defined by substructures, and considering clauses of almost arbitrary length, should be categorized as <rule_learning>.</rule_learning>
11/1		
1172		
1173		
1174		
1175		
1176		
1177		
1178		
1179		
1180		
1181		
1182		
1183		
1184		
1185		
1186		
1187		

# 1188 F.2 ZERO-SHOT W/O PRIOR SUMMARY + VGRL STEP 2

1190	zero-shot predictor LLM CoT we prior Step 2	
191	Inference Step You will use the descriptions below to predict the output of the sizen information about a press includion	zero-snot optimizer LLM CoT wo prior Step 2
192	(b) whith the two observations would be preside and only in or two griefs introduced a needed of the second sec	Optimization Step Your goal is to learn the best descriptions for the model. The model used the Current Pattern Descriptions
193	ment Learning>, < tute_Learning>, < to the starting of the sta	below produced the outputs of the given inputs. ** Current Pattern Descriptions: ** Place of the following induced a state in the state of the following parts have
194	<case_based>: Papers that describe memory-based techniques, case-based reasoning, or design systems in various domains, including structural design of buildings, or discuse goal-driven learning, introspection, and explanation in artificial intelligence, emphasizing learning from specific cases and experiences.</case_based>	rease refer to the following judgement criteria to determine which category the following paper belongs to.
105	<coencil: algorithm="">&gt;: Papers that locus on genetic algorithms for solving large-scale optimization problems, improving solution quality, and exploring crossover operators.  <p< td=""><td><case_based>: Papers that describe memory-based techniques, case-based reasoning, or design systems in various domains, including structural design of buildings, or discuss goal-driven learning, introspection,</case_based></td></p<></coencil:>	<case_based>: Papers that describe memory-based techniques, case-based reasoning, or design systems in various domains, including structural design of buildings, or discuss goal-driven learning, introspection,</case_based>
106	<probabilistic methods="">: No description available. <reinforcement learning="">: Papers that focus on learning, adaptation, and efficient algorithms for playing games against unknown adversaries. <rule learning="">: Papers that discuss techniques and approaches in Inductive Logic Programming</rule></reinforcement></probabilistic>	and explanation in artificial intelligence, emphasizing learning from specific cases and experiences. <genetic_algorithms>: Papers that focus on genetic algorithms for solving large-scale optimization problems, improving solution quality, and exploring crossover operators.</genetic_algorithms>
190	(ILP), such as searching for features defined by substructures and considering clauses of almost arbitrary length: <theory>: Papers that focus on general theories and principles of artificial intelligence, theoretical <theory>: mathematical searchics and around theories are however and theories are discussed as the second secon</theory></theory>	<neural networks="">: Papers that focus on neural networks, their applications, and theoretical perspec- tives, including pruning methods for neural networks.</neural>
197	Consepts, indicements at any for, and comparational boundedness in game takeny; or insching game theory, introduce new classes of adversaries, and provide efficient algorithms for learning to play game against computationally bounded adversaries.	<probabilistic_methods>: No description available. <reinforcement_learning>: Papers that focus on learning, adaptation, and efficient algorithms for planing source to instruct methods.</reinforcement_learning></probabilistic_methods>
198	(Paper Title: Learning from positive data ) (Abstract: Gold showed in 1967 that not even regular grammars can be exactly identified from positive examples alone. Since it is known that children learn natural grammars almost exclusively from positives	- Rule Learning: Papers that discuss techniques and approaches in Inductive Logic Programming (ILP), such as searching for features defined by substructures and considering clauses of almost arbitrary
199	examples, Gold a result has neen used as a tasoretical support for Colomacy's theory of minate numan linguistic abilities. In this paper new results are presented which show that within a Bayesian framework not only grammare, but also logic programs are learnable with arbitrarily low expected error of a learner which maximises	length. <theory>: Papers that focus on general theories and principles of artificial intelligence, theoretical</theory>
200	which does the same from a mixture of positive and argentive examples. An inductive Lapic Programming implementation is described which avails the pitfalls of greedy search by global optimization of this function during the local construction of individual clauses of the hypothesis. Results of testing this implementation on artificially-generated data-sets are reported. These results are in agreement with the	concepts, mathematical analysis, and computational boundedness in game theory, or discuss game theory, introduce new classes of adversaries, and provide efficient algorithms for learning to play games against computationally bounded adversaries.
202	theoretical predictions. ) (Neighbour Summary): The papers cited in this essay discuss the limitations of current inductive logic programming systems in handling noise and learning recursive predicates. A new framework for learning from noisy data and	You are provided with the characteristics of a node, another model's judgment of its category, and its true category. Please optimize the Pattern Descriptions for better prediction.
202	fixed example size is presented, which incorporates a Bayesian heuristic for finding the most probable hypothesis. This approach is implemented in an ILP system called Line, which is shown to handle noise better than other systems like POIL and PROGOL, and is capable of learning from only positive or negative data.	** Inputs (a paper): ** (Paper Title: Learning from positive data )
203	Common points that reflect the category of this paper include: - Handling noise in inductive logic programming systems - Learning recursive predicates - Improving the northyrmance of ILP systems	(Abstract: Gold showed in 1967 that not even regular grammars can be exactly identified from positive examples alone. Since it is known that children learn natural grammars almost exclusively from positives examples Gold's result has been used as a theoretical support for Chomeku's theory of innate human
204	Developing new frameworks for learning from noisy data.)     ** Output Format: **     Please give your output strictly in the following format:	linguistic abilities. In this paper new results are presented which show that within a Bayesian framework not only grammars, but also logic programs are learnable with arbitrarily low expected error from positive
205	Explanations: [Your step-by-step analyses and results] Output: [Pick one in ( <case_based>, <genetic_algorithms>, <neural_networks>, <probabilistic_methods>,</probabilistic_methods></neural_networks></genetic_algorithms></case_based>	examples only. In addition, we show that the upper bound for expected error of a learner which maximises the Bayes' posterior probability when learning from positive examples is within a small additive term of one which does the source forms a mixture of exacting a statement of the source of the
206	<reinforcement_learning>, <rule_learning>, <theory>] , eg. <case_based></case_based></theory></rule_learning></reinforcement_learning>	which does the same from a mixture of positive and negative examples. An inductive Logic Programming implementation is described which avoids the pitfalls of greedy search by global optimisation of this function during the local construction of individual clauses of the bynothesis. Results of testing this
207	Explanations: The paper discusses learning from positive data, specifically within a Bayesian framework, and presents a new approach for learning logic programs from positive examples only. It has compares the performance of its implementation, Lime, with other LEP systems like POLL and PROGOL. The	implementation on artificially-generated data-sets are reported. These results are in agreement with the theoretical predictions. )
208	paper focuses on improving the performance of LLP systems and developing new frameworks for learning from noisy data, which involves learning recursive predicates and handling noise in inductive logic programming systems. Output: "Bub Learning"	(Neighbour Summary: The papers cited in this essay discuss the limitations of current inductive logic programming systems
209		fixed example size is presented, which incorporates a Bayesian heuristic for finding the most probable hypothesis. This approach is implemented in an ILP system called Lime, which is shown to handle noise
210	zero-shot summary LLM CoT wo prior Step 2 Now that you have some descriptions, which will be used as rubrics for the classification task, you need	better than other systems like FOIL and PROGOL, and is capable of learning from only positive or negative data.
211	to summarize and refine them for each category to find the best way to express them. Here are the descriptions: <case_based>: Papers that describe memory-based techniques, case-based reasoning, or design systems</case_based>	Common points that reflect the category of this paper include: - Handling noise in inductive logic programming systems - Learning recursive predicates
212	in various domains, including structural design of buildings, or discuss goal-driven learning, introspection, and explanation in artificial intelligence, emphasizing learning from specific cases and experiences. The papers that focus on case-based reasoning, precedents, and analogy in legal decision-making, proposing models for reasoning with precedents and discussing the challenges of matching appecific case facts with	- Improving the performance of ILP systems - Developing new frameworks for learning from noisy data.)
213	open-textured terms, should be categorized as $<$ Case Based>. The papers that describe learning from specific cases and experiences, such as learning default concepts from observational data, and focus on classifying incompletely described objects, should be categorized as $<$ Case Based>. The papers that describe memorylased technicuse for planning, such as Case Based>. The papers	** The model outputs: ** Rule Learning
214	retrieving and adapting previous planning experiences to solve complex problems, should be categorized as <come based="">. <cometic_algorithms>: Papers that focus on genetic algorithms for solving large-scale optimization </cometic_algorithms></come>	Theory If the model output differs from the target output, update the descriptions for both the model's output
215	Noural Networks, Papere had Kona on mural interaction (her applications, and theoretical perspectives, including pruning methods for neural networks, Chrohading the strain methods for neural networks, Crobabilistic Methods->: No description available. <probabilistic methods-="">: No description available.</probabilistic>	category and the target output category to reduce classification error on both current and future data. If the model and target outputs are the same, update the description for this category only. Limit you New Pattern Descriptions' to less than 150 words per category. Think step by step provide your output
216	<{Rule Learning>: Papers that discuss techniques and approaches in Inductive Logic Programming (ILP), such as searching for features defined by substructures and considering clauses of almost arbitrary length. The papers that focus on inductive logic programming, learning recursive predicates, and	strictly in the following format: ** Output Format: **
217	improving the performance of the system anome on exception at < this Learning <theory: and="" artificial="" focus="" general="" intelligence,="" of="" on="" papers="" principles="" that="" theoretical<br="" theories="">concepts, mathematical analysis, and computational boundedness in game theory, or discuss game theory, introduce new classes of adversaries, and provide efficient algorithms for learning to play games against</theory:>	Piease think step by step and give your outputs strictly in the following format:
218	computationally bounded adversaries. The papers that discuss the development of new frameworks for learning from noisy data, improving the performance of LIP systems, and handling noise in inductive logic programming systems should be categorized as <theory>. The papers with a focus on practical applications of machine learning techniques, such as feature construction, selection, and subset selection,</theory>	[Provide a concise summary of the reasoning process, focusing on the key insights that lead to the final decision. Avoid listing multiple steps. Ensure the reasoning is clear and justifies the new pattern
219	and the use of stochastic techniques, greedy algorithms, and statistical measures should be categorized as <theory>. The papers that discuss theoretical aspects of machine learning, such as the limitations of classical concepts, probabilistic processes, and learning techniques for developing accurate default concerts, should be categorized as <theory>. The maper that focus on theoretical aspects of machine</theory></theory>	descriptions.] New Pattern Descriptions:
220	learning, including learning from examples, noisy data, and uncertain or probabilistic behavior, should be categorized as < Theory>. The papers that focus on theoretical frameworks, probabilistic processes, and learning techniques for addressing complex problems, such as classifying incompletely described	features and insights identified in the input paper. Update the descriptions NOLY for the categories where the model output differs from the target output, or if they match, update ONLY that category. Ensure that
221	orbitist, anoma or categorizes ar < newly rate paper i nations general rates are appresent a rate of the second or artificial intelligence, such as explore their applications in planning and problem-solving, should be categorized as <theorys. as="" aspects="" complexity="" discuss="" in="" learning="" learning,="" machine="" models.<="" of="" paper="" such="" td="" that="" the="" theoretical="" various=""><td>only the following categories are used: <case_based>, <genetic_algorithms>, <neural_networks> <probabilistic_methods>, <reinforcement_learning>, <rule_learning>, <theory>. Each updated</theory></rule_learning></reinforcement_learning></probabilistic_methods></neural_networks></genetic_algorithms></case_based></td></theorys.>	only the following categories are used: <case_based>, <genetic_algorithms>, <neural_networks> <probabilistic_methods>, <reinforcement_learning>, <rule_learning>, <theory>. Each updated</theory></rule_learning></reinforcement_learning></probabilistic_methods></neural_networks></genetic_algorithms></case_based>
222	the importance of representation in inductive learning systems, and the application of multiplicative weight-update rules in on-line prediction models, should be categorized as <free o<="" of="" or="" structure="" system="" systems="" td="" the=""><td>description MUST BE enclosed within <newpattern></newpattern> tags. Only include descriptions for the categories being updated. If the model output and target output are the same, update ONLY that cotogory and NO OUTPES1</td></free>	description MUST BE enclosed within <newpattern></newpattern> tags. Only include descriptions for the categories being updated. If the model output and target output are the same, update ONLY that cotogory and NO OUTPES1
223	is output in the following format: <case based="">: Papers that include [your summary] should be categorized as <case_based>. <genetic_algorithms>: Papers that include [your summary] should be categorized as <ge- netic_Algorithms&gt;:</ge- </genetic_algorithms></case_based></case>	For example: <newpattern><case based="">: The papers with [your new pattern description] should be categorized as</case></newpattern>
224	<neural networks="">: Papers that include [your summary] should be categorized as <neural, networks="">. <probabilistic methods="">: Papers that include [your summary] should be categorized as <probabilistic methods=""><sup>-7</sup> <reinforcement learning="">: Papers that include [your summary] should be categorized as <reinforce-< p=""></reinforce-<></reinforcement></probabilistic></probabilistic></neural,></neural>	<case based="">. <newpattern><genetic algorithms="">: The papers with [your new pattern description] should be catego</genetic></newpattern></case>
225	ment Learning>. <rule learning="">. <theory>: Papers that include [your summary] should be categorized as <rule learning="">. <theory>: Papers that include [your summary] should be categorized as <theory>. Please begin with <start summary="">.</start></theory></theory></rule></theory></rule>	rized as <_Genetic_Algorithms>. as as as Please ONLY reply according to this format, DON'T give me any other words. If the model output and
226	<start_summary> <case_based>: Papers that describe memory-based techniques, case-based reasoning, or design systems in various domains, including structural design of buildings, or discuss available memory in the system.</case_based></start_summary>	target output are the same, update ONLY that category and NO OTHERS. Now take a deep breath and provide a concise and logical Reasoning and New Pattern Descriptions.assistant
1227	and explanation in artificial intelligence, emphasizing learning from specific cases and experiences, case-based reasoning, precedents, analogy in legal decision-making, learning from specific cases and experience, classifying incompletely described objects, learning default concepts from observational	Reasoning: The paper discusses the limitations of current inductive logic programming systems in headling point
202	previous planning experiences to obvec complex problems. <genetic algorithm="">: Repert that focus on genetic algorithms for solving large-scale optimization problems, improving solution quality, and exploring crossover operators.</genetic>	and learning recursive predicates, and presents a new framework for learning from noisy data and fixed example size. The paper also describes an ILP system called Lime, which is shown to handle noise better
1220		than other systems like FOIL and PROGOL, and is capable of learning from only positive or negative data. The key features of this paper include the development of new frameworks for learning from noisy date.
229	playing games against unknown adversaries. «Ruis Learning»: Papers that discuss techniques and approaches in Inductive Logic Programming (ILP), such as earching for features defined by substructures, considering clauses of almost arbitrary length, learning recursive predicates, improving the neufromance of ILP avtems.	aata, improving the performance of LLP systems, and handling noise in inductive logic programming systems. These features are more closely related to theoretical concepts and mathematical analysis, which are characteristic of the <theory> category.</theory>
230	cTheory>: Papers that focus on general theories and principles of artificial intelligence, theoretical concepts, mathematical analysis, and computational boundedness: in game theory, discussing game theory, introducing new classes of adversaries, providing efficient algorithms for learning to play games against computationally bounded advergerize doubloaine dese frameworks for learning to play games against computationally bounded advergerize doubloaine doubloaine for learning to play games against computationally bounded advergerize doubloaine doubloaine for learning to play	New Pattern Descriptions: <newpattern><theory>: The papers that discuss the development of new frameworks for learning</theory></newpattern>
231	noiry data, improving the performance of ILP systems, handling noise in inductive long programming systems, practical applications of machine learning techniques, feature construction, selection, and subset election, use of stochastic techniques, greedy algorithms, statistical amsaures, theoretical aspects	from noisy data, improving the performance of ILP systems, and handling noise in inductive logic programming systems should be categorized as <theoryp.< newpattern=""></theoryp.<>
232	or macanae learning, limitations of classical concepts, probabilistic processes, learning techniques for developing accurate default concepts, learning from examples, noisy data, uncertain or probabilistic behavior, theoretical frameworke, probabilistic processes, learning techniques for addressing complex problem, explanation-based learning, derivational analogy (DA), applications in planning and problem-	<newrauern><kuue_learning>: ine papers that focus on inductive logic programming, learn- ing recursive predicates, and improving the performance of ILP systems should be categorized as <rule learning="">.</rule></kuue_learning></newrauern>
233	retving, complexity of learning in varioux models, importance of representation in inductive learning systems, application of multiplicative weight-update rules in on-line prediction models.	
1234		
235		
236		
237		

### F.3 ZERO-SHOT W/O PRIOR SUMMARY + VGRL STEP 80



- 1294
- 1295

### <sup>1296</sup> G ZERO-SHOT W/ PRIOR SUMMARY + VGRL

#### G.1 ZERO-SHOT W/ PRIOR SUMMARY + VGRL STEP 1

Optimization Step Your goal is to learn the best descriptions for the model. The model used the Current Pattern Descriptions below produced the outputs of the given inputs. \*\* Current Pattern Descriptions: \*\* Please refer to the following judgement criteria to determine which category the following paper belongs Interence Step You will use the descriptions below to predict the output of the given information about a paper including: title, abstract and a summary of information about the papers cited in this paper. You need to tell me which of the following categories this paper belongs to: ed>, <Genetic\_Algorithms>, <Neural\_Networks>, <Probabi ning>, <Rule\_Learning>, <Theory> pattern descriptions and the information about the paper: <Case\_Based>: If the paper discusses the use of past experiences, memory-based techniques, or case retrieval and adaptation processes to solve new problems, classify it as <Case\_Based>. <Genetic Algorithms>: If the paper focuses on optimization techniques inspired by evolutionary pro-cesses, such as population-based search, crossover, and mutation, classify it as <Genetic Algorithms>. <Neural\_Networks>: If the paper covers artificial neural networks, including architectures like feedforward, convolutional, or recurrent networks, and their training methods, classify it as <Neu-ral\_Networks>. We put not strain the second strain the second strain strain the second strain incidenced, consistential, or reserved networks, and their training methods, clearly it as  $<\infty$ -reserved, consistential, which < if the apper discussion methods that we prohabilities: Methods > if the apper discuss methods that we prohabilities: Methods > we consistential that > methods > metho ral\_Networks>. > CProbabilistic Methods>: If the paper discusses methods that use probabilistic models to handle un-certainty, such as Bayesian networks or hidden Markov models, classify it as <Probabilistic Methods>. (Reinforcement Learning): If the paper centers on agents learning from interaction with their en-vironment through trial and error, using techniques like Q-learning or policy gradients, classify it as (Reinforcement\_Learning). < Reinorcement\_learning>: If the paper focuses on extracting interpretable decision rules or patterns, often in the form of "if-then" statements, classify it as <Rule\_Learning>.
< Theory>: If the paper emphasizes theoretical contributions to machine learning or AI, such as mathematical models, complexity theory, or the formal analysis of algorithms, classify it as <Theory>. cons... objects, wis.. ties. To partly `vres which -les mathematical models, complexity theory, or the formal analysis of algorithms, classify it as STepsYou are provided with the characteristics of a node, another model's judgment of its category, and its true category. Please optimize the Pattern Descriptions for better prediction. \*\*\* Inputs (a paper): \*\*\* (Paper Title: Stochastic Propositionalization of Non-Determinate Background Knowledge) (Abstract: It is a well-known fact that propositional learning algorithms require "good" features to perform well in practice. So a major step in data engineering for inductive learning is the construction of good features by domain experts. These features often represent properties of structured objects, where a property typically is the occurrence of a certain substructure having certain properties. To partly automate the process of "feature engineering", we devised an algorithm that teaserhes for fractures which as hinary feature. It differs from existing algorithms in thit is earched is not class-blind, and that it is capable of considering clauses ("context") of almost arbitrary length (size). Preliminary experiments are favorable, and support the view that this approach is promising.) (Neighbour Summary: The papers cited in this essay discuss various techniques and approaches in the field of Dula Learning the field of Du say. Performancy experiments are favorable, and apport the view that this approach is promising.) subgroups "manary: meany discove substant techniques and approaches in the field of Relations,  $\sigma_{\rm prediction}$  productions and the substantiant of the substantiant (MDE) as a substantiant (MDE) as a substantiant of the substantiant of the substantiant of the substantiant (MDE) and the substantiant (MDE) are substantiant (MDE) as a substantiant (MDE) and the substantiant (MDE) are substantiant (MDE) as a substantiant (MDE) are substantiant (MDE) and the substantiant (MDE) are substantiant Output: [Pick one in (<Case\_Based>, <Genetic\_Algorithms>, <Neural\_Networks>, <Probabilistic\_Methods>, <Reinforcement\_Learning>, <Rule\_Learning>, <Theory>]], e.g. <Case\_Based> (size). Preliminary experiments are favorable, and support the view that this approach is promising.) (Neighbour Summary: The papers cited in this essay discuss various techniques and approaches in the field of Rule Learn-ing, specifically in Inductive Logic Programming (ILP). The first paper en-appraises the development of techniques for inverting deduction and introduces Mode-Directed Inverse Entailment (MDIE) as a generalisation and enhancement of previous approaches. The second paper proposes an extension of the feature-vector representation to allow the value of a feature to be a set of strings, which can be efficiently and naturally represented in real-world learning problems. The third paper describes a system learning and ILP.)
\*\* The model outputs: \*\* Rule Learning
\*\* The target outputs: \*\* Rule Learning
If the model output differs from the target output, update the descriptions for both the model's output category and the target output are the same, update the description for this category only. Limit your 'New Pattern Descriptions' to less than 150 words per category. Thisk step by step provide your output strictly in the following format: \*\* Output Format. \*\*
Rule Learning
Rule Learning
If the model outputs if form the target output, update the description for this category only. Limit your 'New Pattern Descriptions' to less than 150 words per category. Think step by step provide your output strictly in the following format: \*\* Output Format. \*\*
Rune: Please ONLY reply according to this format. Do not include any other words or step-by-step breakdow: Now take a deep breath and provide a concise explanation and output.assistant Explanations: The paper discusses the stochastic propositionization of non-determinate backgrow knowledge, which is related to the development of new definitions and methods for prediction algorith The paper also focusses on the analysis of their preformance in various zenamics and the argiptions and the argiption of the prediction is a structure of the prediction of the prediction of the Logic Programming (LEP), which for these supports the connection to Case-Based methods. Output: Chila Laraning> r that you have some descriptions, which will be used as rubrics for the classification task, you need ummarize and refine them for each category to find the best way to express them. Here are the descriptions:  $(Cons_m Based)$ . The papers that feess on the theoretical foundations of neural networks, including the development of new defauttons and matched for prediction algorithms, the analysis of their preformances  $(Cons_m Based)$ . The papers that apply memory-based techniques and can-based resonanting to apply design functions mating, each as using past experiments to all designers in exploring and reflexing design replanation, and introperiors in writeful institutions, emphasizing the neuroflexing design supplication, and introperiors in writeful institutions, emphasizing the neuroflexing of the preformance is a structure of the structure of the institution of the preformance in write the structure of the preformance in various constants, and the exploration of the institution of matching along the structure of the preformance in various constants, and the superscentistical for prediction along the approximation of the preformance in various constants, and the superscentistic of the institution of matching along the approximation in this exploring matching probabilistic models to understant the balancing of prediction allogarithms, the analysis of their preformance. Constant Algorithms : The papers with a factors on genetic algorithms, the analysis  $\sim$  (Constant Algorithms : The papers with a factors on genetic algorithms, including their applications in  $\sim$  (Constant Algorithms : The papers with a factors on genetic algorithms, including their applications in  $\sim$  (Constant Algorithms : The papers with a factors on genetic algorithms including their applications in  $\sim$  (Constant Algorithms : The papers with a factors on genetic algorithms including their applications in  $\sim$  (Constant Algorithms : The papers with a factors of genetic matching the structure of the preformance is the structure of the paper and the factor of the particular in the structure of the paper and the structure of the paper and the structure of the particularities in the structure of the paper and probability models to subcrease the balance of production diperithms and improve their performance, solving optimization problems, graph participation, and other complex problems, and balance to experime the production of the second second second second second second second experimental second second second second second second second second second experiments of the second sec a concise summary of the reasoning process, focusing on the key insights that lead to the ision. Avoid listing multiple steps. Ensure the reasoning is clear and justifies the new pattern [Provide a concise summary of the reasoning process, iocusing on use tay image and the final decision. Avoid listing multiple steps. Ensure the reasoning is clear and justifies the new pattern descriptions.] New Pattern Descriptions: [Please insert your new descriptions here. The new descriptions ONLY for the categories where the model output differs from the input paper. Update the descriptions ONLY for the categories where the model output differs from the target output, or if they match, update ONLY that category. Ensure that only the following categories are used: <Case Based>.<Genetic Algorithms>.<NewTetrn>. Schwidtern>. Schwidte [Provide a final decisi game theory and autoremain maximg, mound or categorisms as < 1000y... Note: Please Offyren services of the category without omissions and NOTHING ELSE! And each category is output in the following format: < Come Basely... <Cose Based>: Papers that include [your summary] should be categorized as <Cose Based>: Generic Algorithm>: Papers that include [your summary] should be categorized as <Ge Normal Networks: Papers that include [your summary] should be categorized as <Nerral, Networks: CProbabilistic, Methods2: Papers that include [your summary] should be extegorized as <Probabilis-ic, Methods2. tic. Methods.). "Reinforcement Learning.": Papers that include [your summary] should be categorized as <Reinfor-ment Learning." Rolin [Learning.]: Papers that include [your summary] should be categorized as <Reinf. "Theory.": Papers that include [your summary] should be categorized as <Theory... Please begin with <CTART\_SUMAIAY.> Please ONLY reply according to this format, DON'T give me any other words. If the model output and target output are the same, update ONLY that category and NO OTHERS. Now take a deep breath and provide a concise and logical Reasoning and New Pattern Descriptions.assistant Charles 1, white .ePCMTP\_10\_LIMEATAVY.
Charles 1, white .ePCMTP\_10\_LIMEATAVY.
Charles 1, Starter 1, Star Reasoning: The input paper discusses the stochastic proposition of non-determinate background knowledge, which involves the construction of features by domain experts and the use of an algorithm to search for features defined by substructures. The paper is related to Rule Learning, specifically in Inductive Logic Programming (ILP), as it discusses techniques and approaches in this field. The model output is Rule Learning, which matches the target output. However, the current pattern descriptions for Rule Learning do not fully capture the essence of the paper. The new pattern descriptions should focus on the key features of the paper, such as the use of stochastic search, the construction of features by domain experts, and the application of ILP techniques. New Pattern Descriptions: <a href="https://www.new.com/domain.com/domain/learning/ Reasoning: 

#### 1350 G.2 ZERO-SHOT W/ PRIOR SUMMARY + VGRL STEP 2 1351

	predictor LLM CoT with prior Step 2	zero-shot optimizer LLM CoT with prior Step 2
Inference You will title, abs	Step are the descriptions below to predict the output of the given information about a paper including: tract and a summary of information about the papers cited in this paper. You need to tell me	Ontimization Step
<pre></pre>	the tonowing exceptions this paper boongs to: awed>. <genetic algorithm="">. <neural networks="">. <probabilistic_methods>. <reinforce- arning&gt;. <rule _learning="">. <theory> he pattern descriptions and the information about the paper:</theory></rule></reinforce- </probabilistic_methods></neural></genetic>	Your goal is to learn the best descriptions for the model. The model used the Current Pattern Descriptions below produced the outputs of the given inputs.
** Patter You will <case_< td=""><td>n Descriptions: ** use the descriptions below. Based&gt;: Papers that focus on the theoretical foundations of neural networks, case-based</td><td>** Current Pattern Descriptions: ** Please refer to the following judgement criteria to determine which category the following paper belongs</td></case_<>	n Descriptions: ** use the descriptions below. Based>: Papers that focus on the theoretical foundations of neural networks, case-based	** Current Pattern Descriptions: ** Please refer to the following judgement criteria to determine which category the following paper belongs
reasonin memory <geneti optimiz</geneti 	g, goal-driven learning, explanation, and introspection in artificial intelligence, and the use of based techniques to support design decision-making, should be categorized as <a href="Coses Based">Coses Based</a> , c Algorithms>: Papers with a focus on genetic algorithms, their applications in solving ation problems, graph partitioning, and other complex problems, should be categorized as	to. <case based="">: Papers that focus on the theoretical foundations of neural networks, case-based</case>
<geneti <neural applicat</neural </geneti 	<ul> <li>Algorithms&gt;.</li> <li>Networks&gt;: Papers that discuss the strengths and weaknesses of neural networks, their ions, connectionist approaches, radial basis function networks, and the convergence of the matrix discussion deputies and the convergence of the strengths.</li> </ul>	reasoning, goal-driven learning, explanation, and introspection in artificial intelligence, and the use of memory-based techniques to support design decision-making, should be categorized as <case_based>.</case_based>
<probal space, fi algorith</probal 	bilistic_Methods>: Papers that discuss the use of mathematical concepts such as version- nite state automata (PSA), and probabilistic models to understand the behavior of prediction ms and improve their performance, should be categorized as <probabilistic_methods>.</probabilistic_methods>	<genetic_algorithms>: Papers with a focus on genetic algorithms, their applications in solving optimization problems, graph partitioning, and other complex problems, should be categorized as <constite algorithms="">:</constite></genetic_algorithms>
<rule_l stochast of "feats</rule_l 	reament_Learning>: There is no summary for this category in the provided text. Learning>: Papers that discuss the application of flattures by domain experts to automate the process is search methods, and the construction of features by domain experts to automate the process are engineering*, and the development of new rules or artistegies based on experience, particularly	Neural_Networks>: Papers that discuss the strengths and weaknesses of neural networks, their applications, connectionist approaches, radial basis function networks, and the convergence of the
in the o <theory of new of womation</theory 	ontext of artificial intelligence, should be categorized as $<$ Rule_Learning>. >:> Papers with a focus on theoretical foundations of machine learning, including the development lefinitions and methods for prediction algorithms, the analysis of their performance in various a and the syndroxinon of their theoretical properties, marituality in the context of same theory	backpropagation algorithm, should be categorized as <neural_networks>. <probabilistic_methods>: Papers that discuss the use of mathematical concepts such as version-</probabilistic_methods></neural_networks>
and adv	erarial learning, should be categorized as <theory>.</theory>	space, finite state automata (FSA), and probabilistic models to understand the behavior of prediction algorithms and improve their performance, should be categorized as <probabilistic methods="">.</probabilistic>
(Abstract examples examples	tite: Learning from positive data ): : Gold showed in 1967 that not even regular grammars can be exactly identified from positive alone. Since it is known that children learn natural grammars almost exclusively from positives , Gold's result has been used as a theoretical support for Chomsky's theory of innate human	<reinforcement_learning>: Inere is no summary for this Category in the provided text. <rule_learning>: Papers that discuss the application of Inductive Logic Programming (ILP) techniques, stochastic search methods, and the construction of features by domain experts to automate the process.</rule_learning></reinforcement_learning>
not only examples the Bayes	abilities. In this paper new results are presented which show that within a Mayesian framework grammars, but also logic programs are learnable with abitrarily low expected error from positive only. In addition, we show that the upper bound for expected error of a learner which maximises $\ell'$ posterior probability when learning from positive examples is within a small additive term of one	of "feature engineering", and the development of new rules or strategies based on experience, particularly in the context of artificial intelligence, should be categorized as <rule_learning>.</rule_learning>
which do implement function implement	es the same from a mixture of positive and negative examples. An Inductive Logic Programming attain in ideerribed which avoids the pitfalls of greedy search by global optimization of this during the local construction of individual clauses of the hypothesis. Results of testing this tation on artificially-generated data-sets are reported. These results are in agreement with the	<theory>: Papers with a focus on theoretical foundations of machine learning, including the development of new definitions and methods for prediction algorithms, the analysis of their performance in various generation and the analysis of their theoretical paperties, particularly in the cartest of grame theory.</theory>
theoretic (Neighbo The pape	al predictions. )	and adversarial learning, should be categorized as <theory>.</theory>
fixed exa hypothes better th	ng noise and isarining recuritive predicates. A new transwork tor isarining from noisy data and mple size is presented, which incorporates a Bayesian heuristic for finding the most probable is. This approach is implemented in an ILP system called Lime, which is shown to handle noise an other systems like FOIL and PROCOL, and it capable of learning from only positive or	You are provided with the characteristics of a node, another model's judgment of its category, and its true category. Please optimize the Pattern Descriptions for better prediction.
negative Common - Handlin - Learnin	data. points that reflect the category of this paper include: g noise in inductive logic programming systems g recursive production logic programming systems	** inputs (a paper): ** (Paper Title: Learning from positive data ) (Abstract: Gold showed in 1967 that not even regular grammars can be evently identified from positive
- Improvi - Develop ** Outpu Please	ng the performance of LLP systems ning new frameworks for learning from noisy data.) t Format: ** we your output strictly in the following format-	examples alone. Since it is known that children lear natural grammars almost exclusively from positives examples, Gold's result has been used as a theoretical support for Chomsky's theory of innate human
Explanat Output:	ions: [Your step-by-step analyses and results]	linguistic abilities. In this paper new results are presented which show that within a Bayesian framework not only grammars, but also logic programs are learnable with arbitrarily low expected error from positive
Pick one <reinfor Please O</reinfor 	im (<_uase_mased>, <genetic_algorithm>, <seural_networks>, <probabilistic_methods>, cement_Learning&gt;, <rule_learning>, <genet_based></genet_based></rule_learning></probabilistic_methods></seural_networks></genetic_algorithm>	examples only. In addition, we show that the upper bound for expected is writin a small additive term of one the Bayes' posterior probability when learning from positive examples is within a small additive term of one which does the same from a mixture of positive and negative gramples. An Inductive I - Department
Now take Explana ically th	a deep breath and provide a concise explanation and output.assistant tions: The paper discusses the theoretical foundations of inductive logic programming, specifi- se development of new frameworks for learning from noise' data and the improvement of ILP	implementation is described which avoids the pitfalls of greedy search by global optimisation of this function during the local construction of individual clauses of the hypothesis. Results of testing this
a new in	. It presents a Bayesian approach for learning from positive examples and compares its perfor- rish other systems. The paper also discusses the limitations of current ILP systems and presents oplementation that avoids greedy search. <rule learning=""></rule>	implementation on artificially-generated data-sets are reported. These results are in agreement with the theoretical predictions. )
Output:		(Neighbour Summary: The papers cited in this essay discuss the limitations of current inductive logic programming systems in bandling noise and learning requisite requiring the systems of the line of the system o
zero-zhot	summary LLM CoT with prior Step 2	fixed example size is presented, which incorporates a Bayesian heuristic for finding the most probable hypothesis. This approach is implemented in an ILP system called Lime, which is shown to handle noise
to summ Here are	witze and refine them for each category to find the best way to express them. the descriptions: Based >: Papers that focus on the theoretical foundations of neural networks one based	better than other systems like FOIL and PROGOL, and is capable of learning from only positive or negative data.
reasonin memory The pap	g, goal-driven learning, explanation, and introspection in a trifficial intelligence, and the use of based techniques to support design decision-making, should be categorized as $<$ Case Based >, ers that focus on case-based reasoning, including the use of precedents, rules, and analogy in	Common points that reflect the category of this paper include: - Handling noise in inductive logic programming systems - Learning recursive predicates
legal de should explana through	cuon-maxing, and the adaptation to mismatches between past experiences and new problems, be categorized as $<$ Cause Basel>. The papers that focus on Cause-Based Planning (CBP), tion-based learning, derivation replay, and the improvement of case similarity judgements feedback should be categorized as $<$ Cause Basel>.	<ul> <li>Learning, recursive predicates</li> <li>Improving the performance of ILP systems</li> <li>Developing new frameworks for learning from noisy data.)</li> </ul>
<geneti optimiz <geneti <neurs< td=""><td>c_Algorithms.): Papers with a focus on genetic algorithms, their applications in solving ation problems, graph partitioning, and other complex problems, should be categorized as c_Algorithms.&gt;. Networks:&gt;: Papers that discuss the strengths and weaknesses of neural networks, their particular and particu</td><td>** The model outputs: ** Rule_Learning</td></neurs<></geneti </geneti 	c_Algorithms.): Papers with a focus on genetic algorithms, their applications in solving ation problems, graph partitioning, and other complex problems, should be categorized as c_Algorithms.>. Networks:>: Papers that discuss the strengths and weaknesses of neural networks, their particular and particu	** The model outputs: ** Rule_Learning
applicat backpro <probab< td=""><td>fore, connectionist approaches, radial basis function networks, and the convergence of the pagation algorithm, should be categorized as <neural networks.<br="">illatic Methods&gt;: Papers that discuss the use of mathematical concepts such as version-space, intervention (2024), add not bability or the statematical to hybridize of methods a statematical statematics of methods as statematical to hybridize of the statematics along the statematical statematics of the statematics along the statematics and the hybridize of the statematics along the statematics and the hybridized to hybridize along the statematics along the statematics and the hybridized to hybridize along the statematics along the statematics along the statematic along the statematic along the statematics along the statematic along the statemati</neural></td><td>** The target outputs: ** Theory If the model output differs from the target output, undate the descriptions for both the model's output</td></probab<>	fore, connectionist approaches, radial basis function networks, and the convergence of the pagation algorithm, should be categorized as <neural networks.<br="">illatic Methods&gt;: Papers that discuss the use of mathematical concepts such as version-space, intervention (2024), add not bability or the statematical to hybridize of methods a statematical statematics of methods as statematical to hybridize of the statematics along the statematical statematics of the statematics along the statematics and the hybridize of the statematics along the statematics and the hybridized to hybridize along the statematics along the statematics and the hybridized to hybridize along the statematics along the statematics along the statematic along the statematic along the statematics along the statematic along the statemati</neural>	** The target outputs: ** Theory If the model output differs from the target output, undate the descriptions for both the model's output
and imp focus on the pres	ex autointra (FON), and productance movies to undiricatal the testation in profit-room equilibrium room their performance, should be categorized as (Probabilistic Methods). The papers with a developing new methods for feature construction, selection, and subset selection, particularly in once of irrelevant features, and exploring the use of stochastic techniques, greedy algorithms, and	category and the target output category to reduce classification error on both current and future data. If the model and target outputs are the same, update the description for this category only. Limit your
statistic papers t perform of predi	al measures to optimize performance, should be categorized as <probabilistic_methods>. The hat discuss the use of probabilistic processes to classify incomplete examples, model underlying ance tasks as probabilistic processes, and apply probabilistic models to understand the behavior ction algorithms, should be categorized as <probabilistic methods="">.</probabilistic></probabilistic_methods>	'New Pattern Descriptions' to less than 150 words per category. Think step by step provide your output strictly in the following format:
<reinfo <rule_1 stochast of "feats</rule_1 </reinfo 	reement' Learning>: There is no summary for this category in the provided text. Learning>: Papers that discuss the application of Inductive Logic Programming (ILP) techniques, ic search methods, and the construction of features by domain experts to automate the process are engineering <sup>2</sup> , and the development of new rules or artitetize based on experience. naticularly	** Output Format: ** Please think step by step and give your outputs strictly in the following format:
in the c discuss and the and the	ontext of artificial intelligence, should be categorized as $<$ Rule Learning>. The papers that the application of Inductive Logic Programming (ILP) techniques, a technatic search whether, construction of features by domain experts to automate the process of "feature engineering". development of new rules or statestics based on eventures.	Reasoning: [Provide a concise summary of the reasoning process, focusing on the key insights that lead to the
artificial recursiv <theory< td=""><td>Intelligence, and the improvement of ILP systems' performance by handling noise and learning predicates, should be categorized as <rale_learning>. &gt; Papers with a focus on theoretical foundations of machine learning, including the development</rale_learning></td><td>final decision. Avoid listing multiple steps. Ensure the reasoning is clear and justifies the new pattern descriptions.]</td></theory<>	Intelligence, and the improvement of ILP systems' performance by handling noise and learning predicates, should be categorized as <rale_learning>. &gt; Papers with a focus on theoretical foundations of machine learning, including the development</rale_learning>	final decision. Avoid listing multiple steps. Ensure the reasoning is clear and justifies the new pattern descriptions.]
scenario theory i theoreti	summanies and sociations for presenction agoritams, the analysis of their performance in various and the exploration of their theoretical properties, particularly in the context of game and adversarial learning, should be categorized as <theory. discuss="" papers="" that="" the="" the<br="">cal foundations of machine learning, including the development of new definitions and methods</theory.>	New rattern Descriptions: [Please insert your new descriptions here. The new descriptions MUST BE DIRECTLY based on the key features and insights identified in the input name. Undate the descriptions ONLY for the extension where
of their and the expected	acuse associations, the analysis of their performance in various scenarios, and the exploration theoretical properties, particularly in the context of game theory and adversarial learning, use of Bayesian frameworks to show the learnability of logic programs with arbitrarily low d error from positive examples only, should be categorized as <theory< td=""><td>the model output differs from the target output, or if they match, update ONLY that category. Ensure that only the following categories are used: <case_based>, <genetic_algorithms>, <neural networks="">,</neural></genetic_algorithms></case_based></td></theory<>	the model output differs from the target output, or if they match, update ONLY that category. Ensure that only the following categories are used: <case_based>, <genetic_algorithms>, <neural networks="">,</neural></genetic_algorithms></case_based>
focus or properti complex theoret	developing new definitions and methods for prediction algorithms, exploring the theoretical set of machine learning algorithms, and discussing the importance of considering the bias and sity of learning algorithms should be categorized as $<$ Theory>. The papers that discuss the cal foundations of machine learning, including the development of naw definitions and $1-d$	<probabilistic methods="">, <reinforcement learning="">, <rule learning="">, <theory>. Each updated description MUST BE enclosed within <newpattern></newpattern> tags. Only include descriptions for the strength of the graduated description and the strength of the strength of</theory></rule></reinforcement></probabilistic>
for pred of their framewo	iction algorithms, the analysis of their performance in various scenarios, and the exploration theoretical properties, particularly in the context of probabilistic processes, pac-learning rks, and knowledge representation, should be categorized as < Theory?. The paper that discuss	Lue categories being updated. If the model output and target output are the same, update ONLY that category and NO OTHERS.] For example:
the theo of their in the c model, a	retucai rounnantoms of marking lincituding the development of new models, the analysis performance in various scenarios exploration of their theoretical properties, particularly ontext of game theory, adversarial learning, and the Probably Approximately Correct (PAC) should be categorized as < Theorem (PAC) and the probability of theoretical foundations of	$<\!\!\rm NewPattern\!\!><\!\!\rm Case\_Based\!\!>:$ The papers with [your new pattern description] should be categorized as $<\!\!\rm Case\_Based\!\!>:<\!\!\rm /NewPattern\!\!>$
machine the anal particul The part	learning, including the development of new definitions and methods for prediction algorithms, splits of their performance in various economics, and the exploration of their theoretical performance in various economics, and the exploration of the development of the economic and the economic and economics are the discuss the theoretical foundations of machine learning, should be categorized as $<$ Theorem.	<newpattern><genetic_algorithms>: The papers with [your new pattern description] should be catego- rized as <genetic_algorithms>.</genetic_algorithms></genetic_algorithms></newpattern>
of new of scenario and adv	lefinitions and methods for prediction algorithms, the analysis of their performance in various s, and the exploration of their theoretical properties, particularly in the context of game theory erarial learning, should be categorized as $<$ Theory>.	Please ONLY reply according to this format, DON'T give me any other words. If the model output and target output are the same undate ONLY that category and NO OTHERS. Now take a deep beach and
Note: Pla is output <case_e< td=""><td>asse ONLY summarize each category without omissions and NOTHING ELSE! And each category in the following format: assed&gt;: Papers that include [your summary] should be categorized as <casebased>.</casebased></td><td>provide a concise and logical Reasoning and New Pattern Descriptions.assistant</td></case_e<>	asse ONLY summarize each category without omissions and NOTHING ELSE! And each category in the following format: assed>: Papers that include [your summary] should be categorized as <casebased>.</casebased>	provide a concise and logical Reasoning and New Pattern Descriptions.assistant
<genetic netic_Al <neural <probab< td=""><td>_augoritamas.: Papers that include [your summary] should be categorized as <ge- gorithms&gt;. Networks&gt;: Papers that include [your summary] should be categorized as <neural_networks>. Jibitic_Methods&gt;: Papers that include [your summary] should be categorized as <probabilis-< td=""><td>Reasoning: The paper discusses the theoretical foundations of learning from positive data, presenting new results</td></probabilis-<></neural_networks></ge- </td></probab<></neural </genetic 	_augoritamas.: Papers that include [your summary] should be categorized as <ge- gorithms&gt;. Networks&gt;: Papers that include [your summary] should be categorized as <neural_networks>. Jibitic_Methods&gt;: Papers that include [your summary] should be categorized as <probabilis-< td=""><td>Reasoning: The paper discusses the theoretical foundations of learning from positive data, presenting new results</td></probabilis-<></neural_networks></ge- 	Reasoning: The paper discusses the theoretical foundations of learning from positive data, presenting new results
tic_Meth <reinfor ment_Le <rule_f< td=""><td>code&gt;</td><td>within a Bayesian framework that show the learnability of logic programs with arbitrarily low expected error from positive examples only. The paper also describes an Inductive Logic Programming implemen- tation that avoids the nitfalls of greedy search by shokel optimization of the function during the local</td></rule_f<></reinfor 	code>	within a Bayesian framework that show the learnability of logic programs with arbitrarily low expected error from positive examples only. The paper also describes an Inductive Logic Programming implemen- tation that avoids the nitfalls of greedy search by shokel optimization of the function during the local
<theory Please be</theory 	>: Papers that include [your summay] should be categorized as <tuse_learning>. gin with <start_summary> SIMMARY&gt;</start_summary></tuse_learning>	construction of individual clauses of the hypothesis. The common points that reflect the category of this paper include handling noise in inductive logic programming systems, learning recursive predicates.
<star <case goal-dri techniqu</case </star 	Based>: Papers that focus on neural networks' theoretical foundations, case-based reasoning, wen learning, explanation, and introspection in artificial intelligence, as well as memory-based ase for design decision-making, case-based planning, explanation-based learning, derivation	improving the performance of ILP systems, and developing new frameworks for learning from noisy data. These points align more closely with the characteristics of the <theory> category, which focuses on</theory>
<pre>replay, <case <geneti optimiv</geneti </case </pre>	and improvement of case similarity judgements through feedback, should be categorized as Based>. c_Algorithms>: Papers with a focus on genetic algorithms and their applications in solving ation problems, graph partitioning, and other complex problems. should be categorized as	theoretical foundations of machine learning, including the development of new definitions and methods for prediction algorithms, the analysis of their performance in various scenarios, and the exploration of their theoretical percenting.
<geneti <neural applicat</neural </geneti 	c Algorithms>. Papers that discuss the strengths and weaknesses of neural networks, their forse, connectionist approaches, radial basis function networks, and the convergence of the magnitum algorithm abundle the extension and a convert. Numerico.	New Pattern Descriptions: <newpattern><theory>: The papers that discuss the theoretical foundations of machine learning.</theory></newpattern>
<pre>content of the second sec</pre>	programme assortiums, anount use categorized as <neural_networks>. bilitic Methods&gt;: Papers that discurs the use of mathematical concepts such as version-space, ate automata (FSA), and probabilistic models to understand the behavior of prediction algorithms row their performance, feature construction, selection, and subset selection, particularly in the</neural_networks>	including the development of new definitions and methods for prediction algorithms, the analysis of their performance in various scenarios, and the exploration of their theoretical properties, particularly
measure model u	of irrelevant features, and the use of stochastic techniques, greedy algorithms, and statistical s to optimize performance, as well as probabilistic processes to classify incomplete examples, anderlying performance tasks as probabilistic processes, and apply probabilistic models to and the behavior of medicina algorithms, should be extensived as "Poshabilistic," Methods	in the context of game theory and adversarial learning, and the use of Bayesian frameworks to show the learnability of logic programs with arbitrarily low expected error from positive examples only, should
<reinfo rized as <rule_1< td=""><td>and use sensitives of prediction algorithms, should be categorized as  (rebablishic Methods), (Reinforcement Learning): Papers that discuss the topic of reinforcement learning should be catego- (Reinforcement Learning): Appendix and the state of the stat</td><td>be categorized as <theory>. <newpattern><rule learning="">: The papers that discuss the application of Inductive Logic Pro- gramming (IL PL techniques etcap-risk methods and the</rule></newpattern></theory></td></rule_1<></reinfo 	and use sensitives of prediction algorithms, should be categorized as  (rebablishic Methods), (Reinforcement Learning): Papers that discuss the topic of reinforcement learning should be catego- (Reinforcement Learning): Appendix and the state of the stat	be categorized as <theory>. <newpattern><rule learning="">: The papers that discuss the application of Inductive Logic Pro- gramming (IL PL techniques etcap-risk methods and the</rule></newpattern></theory>
stochast "feature the cont noise an	ic search methods, the construction of features by domain experts to automate the process of engineering", the development of new rules or strategies based on experience, particularly in text of artificial intelligence, and the improvement of ILP systems' performance by handling d learning recursive predicates, should be categorized as < Rule Learning >>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>	gramming (LF ) techniques, suchastic search methods, and the construction of features by domain experts to automate the process of "feature engineering", and the development of new rules or strategies based on experience, particularly in the context of artificial intelligence. and the improvement of IL-
and an	>: Papers with a focus on theoretical foundations of machine learning, including the development lefinitions and methods for prediction algorithms, the analysis of their performance in various	systems' performance by handling noise and learning recursive predicates, should be categorized as
<theory of new of scenario</theory 	s, the exploration of their theoretical properties, particularly in the context of game theory,	<rule learning="">.<!--/NewPattern--></rule>

# 1404 G.3 ZERO-SHOT W/ PRIOR SUMMARY + VGRL STEP 80

1406	verseshat predictor LIM CoT with prior Step 80	and that antimized LINE (off with union Chap 80
1407	Inference Step	zero-snot optimizer LLM Co1 with prior step 80
1408	You will use the descriptions below to predict the output of the given information about a paper including: title, abstract and a summary of information about the paper cited in this paper. You need to tell me which of the following categories this paper belongs to: <case_based>. <genetic _algorithma="">. <neural, networks="">. <probabilistic _methods="">. <reinforce-< td=""><td>Optimization Step Your goal is to learn the best descriptions for the model. The model used the Current Pattern Descriptions</td></reinforce-<></probabilistic></neural,></genetic></case_based>	Optimization Step Your goal is to learn the best descriptions for the model. The model used the Current Pattern Descriptions
1409	ment Learning>. <rule learning="">. <theory> — — — — — — — — — — — — — — — — — — —</theory></rule>	below produced the outputs of the given inputs. ** Current Pattern Descriptions: ** Please refer to the following judgement criteria to determine which category the following paper belongs
1410	<come_bose(>: Papers that include case-based reasoning, learning from past experiences, adaptation to new situations, recall and adaptation of previously known designs, adaptation knowledge, feature selection, condensation, improving machine learning algorithms efficiency, proposaling new approaches</come_bose(>	to.
1411	synergy between case-based mesoning and constraint satisfaction problems, memory-based techniques, interactive exploration, case-based design systems, case-based problems/outly systems, similarity assessment, incremental learning, adaptation to changing environments, inductive learning systems, Galois latice, classification rules, boolean features, numerical features, finite-state automatic in several	< CaseBased>: rapers that include case-dased reasoning, tearing from past experiences, adaptation to new situations, recall and adaptation of previously known designs, adaptation knowledge, feature selection, condensation, improving machine learning algorithms efficiency, proposing new approaches to anknow preferences applications there are presented in scale world work preshows constraint activitation.
1412	networks, training the free parameters of a scientific model to optimize its accuracy for making huture predictions, prior knowledge, especially in robotic contol systems, case-based classification, lazy learning mechanisms, nearest neighbor classification, registration processes, human-computer systems, and applications in robotics, artificial intelligence, and crisis response planning	synergy between case-based reasoning and constraint satisfaction problems, constraint satisfaction, interactive exploration, case-based design systems, case-based problem-solving systems, similarity
1413	should be categorized as <case based="">. <genetic_algorithms): algorithms,="" artificial="" genetic="" include="" life="" neuro-evolution,<br="" papers="" research,="" that="">solving optimization problems, graph partitioning, complex problems, proposing new approaches to improve performance, applications in theoretical biology and neuro-evolution, genetic algorithms for</genetic_algorithms):></case>	assessment, incremental learning, adaptation to changing environments, inductive learning systems, Galois lattices, classification rules, boolean features, numerical features, finite-state automata in neural
1414	optimization, comparison with other methods, application in machines learning, feature selection, genetic algorithms in robotics, learning classifier systems, evolving biases, decision trees induction algorithm, evolutionary algorithms, novel extensions to existing frameworks, improvements in performance, machine learning techniques, similarity-based case retrieval, inductive decision tree learning, cultural transmission	networks, training the free parameters of a scientific model to optimize its accuracy for making future predictions, prior knowledge, especially in robotic control systems, case-based classification, lazy learning mechanisms, nearest neithbor classification, registration processes, human-computer systems, mixed-
1415	mechanisms, optimization problems, neuro-evolution, online evolution, incremental learning, adaptation to novel situations, applying genetic algorithms to optimize or search for rolutions in complex systems, exploring the effectiveness of various crossover operators, self-organization of feedforward synapses, associative feedback mechanisms, and complex processes for learning non-linearly separable mappings	initiative systems, and applications in robotics, artificial intelligence, and crisis response planning should be categorized as <case_based>.</case_based>
1416	should be categorized as <genetic algorithms="">. <neural networks="">: Papers that include neural networks, connectionist approaches, radial basis function networks, backpropagation algorithm, generative models, decision trees, similarity-based case retrieval, relational reversion, ensemble methods, exoboratory projection purruit, and their applications</neural></genetic>	<genetic algorithms):="" algorithms,="" artificial="" genetic="" include="" life="" neuro-evolution,<br="" papers="" research,="" that="">solving optimization problems, graph partitioning, complex problems, proposing new approaches to improve performance applications in theoretical biology and neuro-evolution genetic algorithms for</genetic>
1417	in areas such as adaptive logic, robotics, dynamic control, and database systems, including those that discuss neural networks' ability to loar and represent complex information, maxively parallel control is a superscription of the structure of the structure of the structure of the control isosities in entropy of the structure of the structure of the structure of the control isosities. Mathematics: Papers(not ong)	optimization, comparison with other methods, application in machine learning, feature selection, genetic algorithms in robotics, learning classifier systems, evolving biases, decision tree induction algorithm, evolutionary algorithms, novel extensions to existing frameworks, improvements in performance, machine
1418	** Laput: ** (Paper Tike: Cognitive Computation (Extended Abstract)) (Abstract: Cognitive computation is discussed as a discipline that links together neurobiology, cognitive psychology and artificial intelligence.)	learning techniques, similarity-based case retrieval, inductive decision tree learning, cultural transmission mechanisms, optimization problems, neuro-evolution, online evolution, incremental learning, adaptation to novel situations, applying genetic algorithms to optimize or search for solutions in complex systems,
1419	(Neighbour Summary: The papers cited in this easy discuss the concept of learning and reasoning, specifically focusing on the Probably Approximately Correct (PAC) learning model and its generalizations. The authors investigate the idea of agontic Learning, where minimal assumptions are made about the target functions, and explore	exploring the effectiveness of various crossover operators, self-organization of feedforward synapses, associative feedback mechanisms, and complex processes for learning non-linearly separable mappings should be categorized as <genetic algorithms="">.</genetic>
1/121	the possibilities or this approach tarong various results and sugerithms. Ine paper and outer on the Learning to Reason fravework, which combines learning and reasoning just a single task, and examine the tradeoff between learnability, oracle strength, and reasoning query range. Overall, the cited papers contribute to the understanding of learning and reasoning in artificial intelligence.)	<neural_networks>: Papers that include neural networks, connectionist approaches, radial basis function networks, backpropagation algorithm, generative models, decision trees, similarity-based case</neural_networks>
1422	Despin commat: Please give your output strictly in the following format: 	retrieval, relational regression, ensemble methods, exploratory projection pursuit, and their applications in areas such as adaptive logic, robotics, dynamic control, and database systems, including those that discuss neural networks' ability to learn and represent complex information. massively parallel
1423	Pickone in ( <case based="">, <genetic_algorithms>, <neural_network>, <probabilistic_methods>, <reinforcement_learning>, <rule_learning>, <theory>)], e.g. <case based=""> Please ONLY works yccoreding to this formula D. not initiation are the matter in the state of the sta</case></theory></rule_learning></reinforcement_learning></probabilistic_methods></neural_network></genetic_algorithms></case>	processing, incremental learning, and applications in areas such as adaptive logic, robotics, and dynamic control should be categorized as <neural networks="">.</neural>
1424	Now take a deep break and provide a concise explanation and output assistant Explanations: The paper discusses cognitive computation as a discipline that links meurobiology cognitive paychology, and artificial intelligence. The cited names force on leaving and encoders	<pre><rromabilistic_methods>: Papers(too long) You are provided with the characteristics of a node, another model's judgment of its category, and its</rromabilistic_methods></pre>
1425	specifically the PAC learning model and its generalizations, agnostic learning, and the Learning to Reason framework. These topics are related to probabilistic methods, which involve making predictions or decisions based on probability distributions. Output: Crobabilities, Methods>	true category. Please optimize the Pattern Descriptions for better prediction. ** Inputs (a paper): ** (Paper Title: Computing (Extended Abstract))
1426	zero-shot summary LLM CoT with prior Step 80	(Abstract: Cognitive computation is discussed as a discipline that links together neurobiology, cognitive psychology and artificial intelligence. )
1427	Now that you have some descriptions, which will be used as rubrics for the classification task, you need to summarize and refine them for each category to find the best way to express them.	(Neignoour Summary: The papers cited in this essay discuss the concept of learning and reasoning, specifically focusing on the Probably Approximately Correct (PAC) learning model and its generalizations. The authors investigate
1428	Here are the descriptions: < <pre>c<pre>c</pre>are the include case-based removing. learning from past experiences, adaptation to new intrastions, recall and adaptation of previously known dougns, adaptation knowledge, feature subscition, condempation, improving machine learning almosthum adiptioner, nonovalues new suproaches</pre>	the idea of agnostic learning, where minimal assumptions are made about the target function, and explore the possibilities of this approach through various results and algorithms. The papers also touch on the Learning to Resear framework, which combined learning and rescaping into a circle task, and examined
1429	to enhance performance, applying these approaches in real-world problems, constraint asticfaction, eynergy between case-based reasoning and constraint asticfaction problems, memory-based techniques, interactive exploration, case-based design systems, case-based problem-solving systems, similarity assessment, incremental learning, adaptation to changing environments, inductive learning revelems.	the tradeoff between learnability, oracle strength, and reasoning query range. Overall, the cited papers contribute to the understanding of learning and reasoning in artificial intelligence.)
1430	Galoic lattices, classification rules, boolean festures, numerical features, finite-state automats in neural networks, training the free parameters of a zeientific model to optimise its accuracy for making future predictions, prior knowledge, especially in robotic control systems, case-based classification, largi karning mechanisms, nearest neighbor classification, registration processes. Juman-computer systems, mixed-	** The model outputs: ** Probabilistic_Methods ** The target outputs: **
1431	initiative systems, and applications in robotics, artificial intelligence, and crisis response planning should be categorized as <case_bases<sup>1&gt;. The papers that integrate case-based reasoning techniques with other reasoning methods, such as constraint reasoning, for solving complex problems, especially in domain like environmental decision support reasons, should be categorized as <case_based>.</case_based></case_bases<sup>	Neural Networks If the model output differs from the target output, update the descriptions for both the model's output
1432	The papers that focus on Case-Based Reasoning. Classification Methodologies, Inductive Learning, and Knowledge Discovery, such as learning from past experiences, adaptation to new situations, and generating classification rules from data, should be categorized as < Case Based>. <genetic algorithms,="" algorithms::="" attificatific="" genetic="" include="" neuro-evolution,<="" papers="" research,="" td="" that=""></genetic>	category and the target output category to reduce classification error on both current and future data. If the model and target outputs are the same, update the description for this category only. Limit your 'New Pattern Descriptions' to less than 150 words per category. Think step by step provide your output
1433	improve performance, applications in theoretical biology and neuro-evolution, genetic algorithms for optimization, comparison with other methods, application in machine learning, feature selection, genetic algorithms in robotics, hearning classifier systems, evolving biases, decision tree induction algorithm, evolutionary algorithms, novel extensions to oxising frameworks, improvements in performance, machine	strictly in the following format: ** Output Format: ** Please think step by step and give your outputs strictly in the following format:
1434	learning techniques, similarity-based case retrieval, inductive decision tree learning, cultural trans- mission mechanizms, optimization problem, neuro-volution, online evolution, incremental learning, adaptation to novel situations, applying genetic algorithms to optimize or search for solutions in complex systems, exploring the effectiveness of various crossover operators, self-organization of feedforward	Reasoning: IProvide a consist summary of the reasoning process. Sourcing on the law insights that lead to the
1435	synapses, associative feedback mechanisms, and complex processes for learning non-linearly separable mappings should be categorised as <genetic_algorithms< td=""><td>I forthe a concise summary of the reasoning process, focusing on the key magnits that read to the final decision. Avoid listing multiple steps. Ensure the reasoning is clear and justifies the new pattern descriptions.] New Pattern Decemption:</td></genetic_algorithms<>	I forthe a concise summary of the reasoning process, focusing on the key magnits that read to the final decision. Avoid listing multiple steps. Ensure the reasoning is clear and justifies the new pattern descriptions.] New Pattern Decemption:
1430	Case-Based Reasoning should be categorized as <genetic algorithms="">. <neural networks="">: Papers that include neural networks, connectionist approaches, radial basis function networks, backpropagation algorithm, generative models, decision trees, similarity-based case retrieval, relational regression, ensemble methods, exploratory projection pursuit, and their applications</neural></genetic>	Please insert your new descriptions here. The new descriptions MUST BE DIRECTLY based on the key features and insights identified in the input paper. Update the descriptions ONLY for the categories where
1437	in areas such as adaptive logic, robotics, dynamic control, and database systems, including those that discus neural networks' ability to learn and represent complex information, maxievely parallel processing, incremental learning, and applications in areas such as adaptive logic, robotics, and dynamic control should be categorized as <	the model output differs from the target output, or if they match, update ONLY that category. Ensure that only the following categories are used: <case_based>, <genetic_algorithms>, <neural_networks>, <probabilistic methods="">, <reinforcement learning="">, <rule learning="">, <theory>. Each updated</theory></rule></reinforcement></probabilistic></neural_networks></genetic_algorithms></case_based>
1439	Note: Please ONLY summarize each category without omizions and NOTHING ELSE! And each category is output in the following format: <case< math=""> Based&gt;: Papers that include [your summary] should be categorized as <math><case< math=""> Based&gt;: <math><case all_{a}<="" math=""> Appointmas': Papers that include [your summary] should be categorized as <math><ga-< math=""></ga-<></math></case></math></case<></math></case<>	description MUST BE enclosed within <newpattern></newpattern> tags. Only include descriptions for the categories being updated. If the model output and target output are the same, update ONLY that category and NO OTHERS.]
1440	CNeural Networks>: Papers that include [your summary] should be categorized as <neural networks="">. <probabilistic <probabilistic<br="" [your="" as="" be="" categorized="" include="" methods:="" papers="" should="" summary]="" that="">the Methods?</probabilistic></neural>	For example: <newpattern><case_based>: The papers with [your new pattern description] should be categorized as <cose_based>: <newpattern></newpattern></cose_based></case_based></newpattern>
1441	ment_learning>, repress that include your summary provide the extegorized as <reinforce- ment_learning&gt;, repress that include your summary should be extegorized as <rule_learning>, Plane bergin with <traine summary="">.</traine></rule_learning></reinforce- 	<pre></pre> <pre>&lt;</pre>
1442	<start summary=""> <case based="">: Papers that include case-based reasoning, learning from past experiences, adaptation to new rituations, recall and adaptation of previously known designs, adaptation knowledge, feature</case></start>	Please ONLY reply according to this format, DON'T give me any other words. If the model output and target output are the same, update ONLY that category and NO OTHERS. Now take a deep breath and
1443	seecton, condensation, improving machine learning algorithms efficiency, propasing new approaches to enhance performance, applying these approaches in this efficiency improvements and action synergy between case-based reasoning and constraint antifaction problems, memory-based techniques, interactive exploration, case-based problems, based problems, and and the second syntheses, similarity	provide a concise and logical Reasoning and New Pattern Descriptions.assistant
1444	sessessment, incremental searing, anaptation to cranging environments, inductive learning systems, Galois latices, chaorifaction rules, toolean features, numerial features, finite-state automata in neural networks, training the free parameters of a acientific model to optimize its accuracy for making future predictions, prior knowledge, especially in robotic control systems, case-based classification, lary	The paper discusses cognitive computation as a discipline that links neurobiology, cognitive psychology, and artificial intelligence. The neighbor summary highlights the concept of learning and reasoning,
1445	minedia misamante, masa at angkanit tatarankan, regin tinto pinesawa, animisi comparas synomia, minedia minedia minedia angkanika na angkanika na na katakan na katakan na katakan na katakan na katakan na kat <genetica agontima=""> Papers that include genetic algorithms, artificial life research, neuro-evolution, solving optimization problems, graph partitioning, complex probleme, proposing new approaches to</genetica>	specifically focusing on the Probably Approximately Correct (PAC) learning model and its general- izations. This indicates that the paper is more related to neural networks, which are a key aspect of artificial intelligence and cognitive computation. The model output, Probabilistic Methods, does
1446	miljetive je na oznamasti, naprača odko zr vilovita na bitovita v nistno-bevenatana, gotova c lagio na met ko optimizati i a repartava usila nje venačnosta, popilara na bitovita pravina poslava i poslava na poslava se obrava na poslava poslava se obrava poslava poslav poslava poslava p	not match the target output, Neural_Networks, suggesting that the current pattern descriptions for Probabilistic_Methods are too broad and need to be updated to better capture the characteristics of
1447	mechanisms, optimization problems, neuro-evolution, online evolution, incremental learning, dispration sephoring the effectiveness of various crossover operators, self-organization of feedforward sympose, associative feedback mechanisms, and consider properties for learning evolution. Investmental e-	papers related to neural networks. New Pattern Descriptions: <newpattern><probabilistic methods="">: The papers that discuss Probably Approximately Correct</probabilistic></newpattern>
1448	<td>(PAC) learning models, agnostic learning, and the tradeoff between learnability, oracle strength, and reasoning query range should be categorized as <probabilistic_methods>.</probabilistic_methods></td>	(PAC) learning models, agnostic learning, and the tradeoff between learnability, oracle strength, and reasoning query range should be categorized as <probabilistic_methods>.</probabilistic_methods>
1449	that discuss neural networks' ability to learn and expressed complex information, maxivaly parallel processing, incremental learning, and applications in areas such as adaptive logic, robotics, and dynamic ("Perchalitation Markoto"). Parame that discuss Problem Amazona ("Amazon").	<newpattern><neural_networks>: The papers that link neurobiology, cognitive psychology, and artificial intelligence, and discuss the concept of learning and reasoning in artificial intelligence should be categorized as <neural networks="">: </neural></neural_networks></newpattern>
1450	agnostic learning, and the tradeoff between(too long)	
1451		
1452		
1453		
1454		