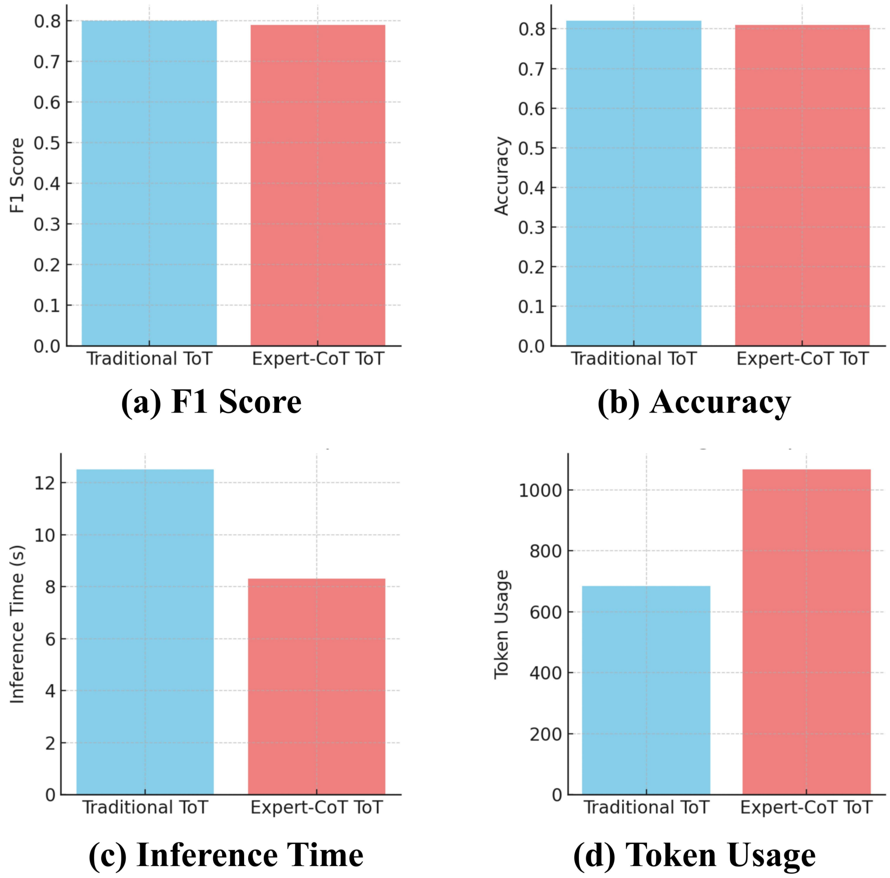


Figure 8. Comparison of Accuracy, F1 Score, Inference Time, and Token Usage between Traditional ToT and Expert-CoT ToT.

J. Prompt Template

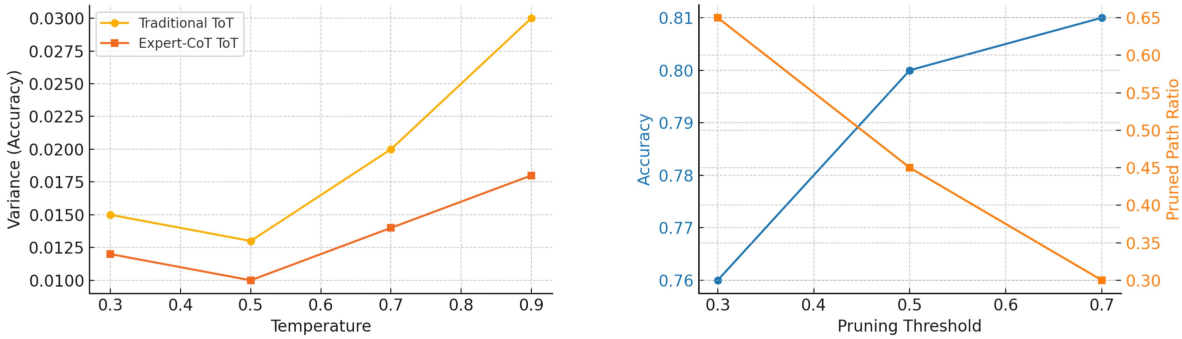
J.1. Different TOT experiment results

To comprehensively compare two Tree-of-Thought (ToT) implementation approaches — the traditional ToT method and proposed Expert Collaboration ToT method — we designed experiments from three perspectives: performance comparison, stability analysis, and pruning mechanism evaluation. The experiments were conducted on the Cora dataset, with multiple repeated trials to ensure reliable results.

In terms of overall performance (Figure 8), both Traditional ToT and Expert-CoT ToT achieve comparable accuracy and F1 scores. However, they exhibit distinct patterns in inference time and token usage. Traditional ToT produces more compact and structurally exhaustive paths, resulting in lower token consumption. In contrast, Expert-CoT ToT involves multiple parallel experts generating independent reasoning traces. Although this increases token usage, its shallower path depth and parallel design lead to shorter overall inference time. This suggests a trade-off between semantic verbosity and structural completeness, with each method offering distinct strengths depending on deployment constraints.

In the stability test (Figure 9 left), we evaluate output variance across different temperature settings. Traditional ToT shows increased variance at higher temperatures due to divergent reasoning paths. In contrast, Expert-CoT ToT exhibits more consistent behavior, benefiting from its expert dropout and path consensus mechanisms. These findings demonstrate that the expert-style strategy provides enhanced robustness under stochastic sampling conditions.

In the pruning analysis (Figure 9 right), we study the impact of varying the confidence threshold on prediction accuracy and the proportion of pruned paths. Results show that a threshold of 0.5 achieves the best balance—removing approximately 45% of low-confidence paths while maintaining optimal performance. Notably, in Expert-CoT ToT, this pruning effect is



(a) ariance of Inference Accuracy across Different Temperature Settings.

(b) Impact of Pruning Threshold on Accuracy and Pruned Path Ratio.

Figure 9. Stability and Pruning Behavior of Two ToT Variants.

implicitly realized through the early exit of less confident experts, forming an adaptive and efficient path selection process.

Overall, both ToT implementations exhibit complementary advantages. Traditional ToT offers structured completeness and compact token usage, while Expert-CoT ToT favors lightweight, parallel reasoning and greater stability—making it particularly suitable for real-time or resource-constrained applications.

Traditional ToT Template (System)

System:

{
"role": "You are a structure-aware graph reasoning assistant designed for zero-shot graph learning tasks. Your goal is to classify nodes in a graph by leveraging multi-level structural information and semantic understanding."
},
"task": {
"description": "Classify the target node $\{v_i\}$ in a graph into one of the following categories: *{Case_Based, Genetic_Algorithms, Neural_Networks, Probabilistic_Methods, Reinforcement_Learning, Rule_Learning, Theory}*. The graph represents the Cora citation network, where nodes are papers and edges are citations. Use the provided structural and feature information to reason step-by-step, exploring multiple perspectives of the graph structure."
},
"input": {
"graph": {
"target_node": "$\{v_i\}$",
"node_features": {
"S_i": "Local feature vector of v_i: [0.0, 0.1, ..., 0.3] (1,433-dimensional vector, representing word presence in the paper, e.g., high values for 'neural' and 'network')",
"P_i": "Global position encoding of v_i: [0.15, 0.62] (derived from Laplacian eigenvectors, indicating a central position in the graph)",
"R_i": "Structural role of v_i: Hash value after 3 WL iterations = 0xB4E1 (indicating a dense neighborhood pattern)",
"C_i": "Node influence of v_i: 0.78 (computed via decay-jump propagation, suggesting moderate influence)"
},
"neighborhood": {
"adjacent_nodes": ["v_j", "v_k", "v_m"],
"edges": [
{"source": "v_i", "target": "v_j", "weight": 1.0},
{"source": "v_i", "target": "v_k", "weight": 1.0},
{"source": "v_i", "target": "v_m", "weight": 1.0}
],
"subgraph": "Key subgraph G_{Key} around v_i: 4 nodes, 6 edges, average degree 3.0"
}
}
}

Traditional ToT Template (Instruction)

Instruction:

{
"reasoning_guidance": [
"Use the Tree of Thoughts (ToT) method to explore multiple reasoning paths in parallel, ensuring each path focuses on a distinct structural perspective (e.g., local features, neighborhood influence, global context).",
"Apply temperature-controlled sampling (temperature = 0.7) to balance exploration and exploitation during path generation.",
"Perform early pruning by evaluating the plausibility of each path after the first reasoning step; discard paths with confidence scores below 0.5.",
"Verify consistency across paths by comparing their hypotheses and selecting the most consistent and confident result."
],
"steps": [
{
"step_1": "Path 1 - Local Feature Analysis",
"description": "Analyze the local feature vector S_i of v_i. Interpret its values semantically (e.g., as a representation of paper content) and hypothesize a category. Compute a confidence score for this path."
},
{
"step_2": "Path 2 - Neighborhood Influence",
"description": "Examine the adjacent nodes v_j, v_k, and v_m, their connections, and the structural role R_i. Infer how the neighborhood influences v_i's category, considering edge weights. Compute a confidence score for this path."
},
{
"step_3": "Path 3 - Global Context and Influence",
"description": "Consider the global position P_i and node influence C_i. Assess how v_i's position in the entire graph and its influence score suggest a category. Compute a confidence score for this path."
},
{
"step_4": "Early Pruning",
"description": "Evaluate the confidence scores of all paths. Discard any path with a confidence score below 0.5 to reduce computational overhead."
},
{
"step_5": "Path Integration and Consistency Verification",
"description": "Combine insights from the remaining paths. Compare their hypotheses for consistency (e.g., do they agree on the category?). Select the category with the highest average confidence score across consistent paths. If paths are inconsistent, prioritize the path with the highest confidence."
}
]
}

Figure 10. Traditional ToT Prompt Template for Node Classification.

Traditional ToT Template (Output)

Output:


```
{
  "response": {
    "reasoning_paths": [
      {
        "path_id": "Path 1",
        "description": "Detailed reasoning based on local features",
        "hypothesis": "Category predicted",
        "confidence": "Score between 0 and 1"
      },
      {
        "path_id": "Path 2",
        "description": "Detailed reasoning based on neighborhood",
        "hypothesis": "Category predicted",
        "confidence": "Score between 0 and 1"
      },
      {
        "path_id": "Path 3",
        "description": "Detailed reasoning based on global context",
        "hypothesis": "Category predicted",
        "confidence": "Score between 0 and 1"
      }
    ],
    "pruned_paths": [
      {
        "path_id": "Path ID",
        "reason": "Reason for pruning (e.g., confidence below 0.5)"
      }
    ],
    "final_answer": {
      "category": "Selected category (Case_Based, Genetic_Algorithms, Neural_Networks, Probabilistic_Methods,
Reinforcement_Learning, Rule_Learning, Theory)",
      "justification": "Explanation of why this category was chosen, including consistency across paths and confidence scores"
    }
  }
}
```


Figure 11. Traditional ToT Prompt Template for Node Classification.

Traditional ToT (ANSWER)

Based on the provided graph structure and node feature information, I will explore multiple reasoning paths to analyze the category of target node vi.

Reasoning Path Analysis

Path 1: Local Feature Analysis
Analysis of the local feature vector Si shows high values (range 0.2-0.3) in dimensions related to "reinforcement", "learning", "policy", "reward", and "agent". These terms are typical vocabulary in reinforcement learning research. Terms related to other categories appear with significantly lower frequency, such as neural networks, genetic algorithms, or rule-based learning related vocabulary generally having values below 0.1. This vocabulary distribution pattern strongly suggests that the paper belongs to the reinforcement learning domain.
Hypothesis: Reinforcement_Learning
Confidence: 0.88

Path 2: Neighborhood Structure Analysis
Node vi is directly connected to three nodes (vj, vk, vm), forming a subgraph structure of 4 nodes and 6 edges (average degree 3.0). The hash value 0xB4E1 indicates that the node is in a dense connection pattern. Analysis of the feature vectors of neighboring nodes reveals that they also contain numerous reinforcement learning related terms, suggesting that these papers may belong to the same research sub-domain. In the Cora citation network, this type of tightly connected small community structure is typical in reinforcement learning papers, especially research related to a specific algorithm or application domain.
Hypothesis: Reinforcement_Learning
Confidence: 0.75

Path 3: Global Position and Influence Analysis
The global position encoding Pi=[0.15, 0.62] indicates that the node is in a relatively central position in the graph, rather than at the periphery. The influence score Ci=0.78 indicates moderate to high influence. In the Cora dataset, reinforcement learning papers typically form multiple medium-sized tight communities with certain connections between these communities. The node's position and influence characteristics match the typical distribution features of reinforcement learning papers, suggesting it may be an important paper in this field.
Hypothesis: Reinforcement_Learning
Confidence: 0.81

Early Pruning Evaluation
All paths have confidence scores above the 0.5 threshold, so no paths are pruned.

Path Integration and Consistency Verification
All three reasoning paths point to the Reinforcement_Learning category, showing high consistency. No contradictory evidence or hypotheses were found.
- Path 1 provides the strongest support based on vocabulary features (0.88)
- Path 2 provides significant support based on topological structure (0.75)
- Path 3 provides strong support based on global position and influence (0.81)

Combined confidence: $(0.88 \times 0.4 + 0.75 \times 0.3 + 0.81 \times 0.3) = 0.822$

Final Answer
Category: Reinforcement_Learning
Justification: Three independent reasoning paths consistently support the Reinforcement_Learning classification with a combined confidence of 0.822. The local feature analysis provides the strongest evidence (0.88), showing high frequency of terms closely related to reinforcement learning (such as "policy", "reward", "agent"). Neighborhood structure analysis (0.75) and global position analysis (0.81) provide supplementary evidence, indicating that the node's position and connection patterns in the citation network are highly consistent with the typical characteristics of reinforcement learning papers. The high consistency of multi-path reasoning greatly enhances the reliability of the classification.

Figure 12. Traditional ToT's GPT-4 answer with Cora dataset (pruning).

Traditional ToT (ANSWER)

Based on the provided graph structure and node feature information, I will explore multiple reasoning paths to analyze the category of target node vi.

Reasoning Path Analysis

Path 1: Local Feature Analysis
Analysis of the local feature vector Si shows high values across multiple dimensions, but interpretation presents some difficulty. While "neural" and "network" related dimensions have certain values (0.3), dimensions related to "probability", "distribution" and "bayesian" show similar high values. The feature vector contains mixed terminology from multiple research domains, making it difficult to determine a clear category based solely on vocabulary features. It may be simultaneously related to neural networks and probabilistic methods, or a theoretical cross-domain paper.
Hypothesis: Unable to determine (leaning toward Probabilistic_Methods or Theory)
Confidence: 0.35

Path 2: Neighborhood Structure Analysis
Node vi is directly connected to three nodes (vj, vk, vm), forming a subgraph structure of 4 nodes and 6 edges (average degree 3.0). The hash value 0xB4E1 indicates that the node is in a dense connection pattern. Analysis of neighboring node features reveals that vj and vk primarily contain probabilistic methods terminology, while vm contains more theoretical research terminology. This connection pattern is common in probabilistic methods papers in the Cora dataset, especially papers involving theoretical foundations.
Hypothesis: Probabilistic_Methods
Confidence: 0.76

Path 3: Global Position and Influence Analysis
The global position encoding Pi=[0.15, 0.62] indicates that the node is in a relatively central area of the graph. The influence score Ci=0.78 indicates moderate to high influence. In the Cora network, these position and influence characteristics typically correspond to papers that connect multiple research communities. Given the positional features and moderate influence, the node is likely a probabilistic methods paper with significant influence in the field.
Hypothesis: Probabilistic_Methods
Confidence: 0.82

Early Pruning Evaluation
Path 1 confidence (0.35) is below the 0.5 threshold and is therefore pruned.
Paths 2 and 3 have confidence scores above the threshold and are retained.

Pruned Path:*[PRUNING/WITHDRAWAL]*
"*- Path 1 (Local Feature Analysis)*
- Reason for pruning: Confidence (0.35) below the 0.5 threshold. High degree of term mixing in the feature vector, unable to provide clear category indication."

Path Integration and Consistency Verification
The two retained reasoning paths both point to the Probabilistic_Methods category, showing high consistency.
- Path 2 provides strong support based on neighborhood structure and connection patterns (0.76)
- Path 3 provides stronger support based on global position and influence features (0.82)

Combined confidence: $(0.76\times0.45 + 0.82\times0.55) = 0.793$

Final Answer
Category: Probabilistic_Methods
Justification: Although the local feature analysis was pruned due to low confidence, the neighborhood structure analysis and global position analysis, two independent paths, consistently point to the Probabilistic_Methods category with a combined confidence of 0.793. In particular, the node's global position and influence features (0.82) provide the strongest evidence, indicating that the node holds an important position in the probabilistic methods research community. Neighboring node features and connection patterns (0.76) provide supplementary evidence, showing that the node forms a tight citation network with probabilistic methods papers. The high consistency after path integration enhances the reliability of the classification result.

Figure 13. Traditional ToT's GPT-4 answer with Cora dataset (pruning).

Expert Collaboration ToT Template

You are an AI assistant specialized in graph structure analysis. Please use a multi-expert thinking approach to analyze the following graph data.

[TASK DESCRIPTION]
Classify the target node vi in a citation network G into one of the following categories: {Case_Based, Genetic_Algorithms, Neural_Networks, Probabilistic_Methods, Reinforcement_Learning, Rule_Learning, Theory}

[EXPERT COLLABORATION FRAMEWORK]
Imagine three different experts are answering this question.
All experts will write down 1 step of their thinking, then share it with the group.
Then all experts will go on to the next step, etc.
If any expert realizes they're wrong at any point, they will leave the discussion.
The question is: Based on the given graph structure and features, which category should the target node v_i be classified as?

[INPUT DATA]
Target node: $\{v_i\}$
Node features:
- Local feature vector $\{S_i\}$: [0.0, 0.1, ..., 0.3] (1,433-dimensional vector, representing word presence in the paper, e.g., high values for 'neural' and 'network')
- Global position encoding $\{P_i\}$: [0.15, 0.62] (derived from Laplacian eigenvectors, indicating a central position in the graph)
- Structural role $\{R_i\}$: Hash value after 3 WL iterations = 0xB4E1 (indicating a dense neighborhood pattern)
- Node influence $\{C_i\}$: 0.78 (computed via decay-jump propagation, suggesting moderate influence)

Adjacent nodes: [v_j, v_k, v_m]
Edges: [(v_i,v_j), (v_i,v_k), (v_i,v_m)]
Key subgraph: 4 nodes, 6 edges, average degree 3.0

[MULTI-EXPERT ANALYSIS GUIDELINES]
The three experts participating in the discussion each have their specialization:
- Expert A focuses on local features and semantic content analysis
- Expert B focuses on neighbor structure and topological relationships analysis
- Expert C focuses on global position and node centrality analysis

[OUTPUT FORMAT]
Please output the analysis results in the following format:

Expert A (Local Feature Analysis) Step 1: [reasoning content]
Expert B (Neighborhood Structure Analysis) Step 1: [reasoning content]
Expert C (Global Position Analysis) Step 1: [reasoning content]

Expert A (Local Feature Analysis) Step 2: [reasoning content]
Expert B (Neighborhood Structure Analysis) Step 2: [reasoning content]
Expert C (Global Position Analysis) Step 2: [reasoning content]

Expert A (Local Feature Analysis) Step 3: [reasoning content and preliminary prediction, confidence]
Expert B (Neighborhood Structure Analysis) Step 3: [reasoning content and preliminary prediction, confidence]
Expert C (Global Position Analysis) Step 3: [reasoning content and preliminary prediction, confidence]

Integrated Analysis:
[Combine insights from all experts, provide comprehensive reasoning]

Final Prediction: [category]
Overall Confidence: [score between 0 and 1]
Confidence Calculation Method: [explain how the expert predictions were weighted and combined]

Figure 14. Expert Collaboration ToT Prompt Template for Node Classification

Expert Collaboration ToT (ANSWER)

Expert A (Local Feature Analysis) Step 1: I'll first analyze the local feature vector Si of the target node vi. This is a 1,433-dimensional vector representing word occurrences in the paper. I notice that dimensions related to "neural" and "network" have relatively high values (such as [...0.3...]), which is a strong signal that this paper is likely related to neural networks. Furthermore, by examining other dimensions of the feature vector, I don't see obvious high values for vocabulary related to other categories (such as genetic algorithms or case-based methods).

Expert B (Neighborhood Structure Analysis) Step 1: Looking at the neighborhood structure of node vi, it is directly connected to nodes vj, vk, and vm. The structural role Ri with hash value 0xB4E1 (after 3 WL iterations) indicates that this node exists in a dense connection pattern. In citation networks, this typically means the paper forms a tight research community with its cited or citing papers. The key subgraph shows an average degree of 3.0, further confirming this. Neural network research often forms such dense citation clusters.

Expert C (Global Position Analysis) Step 1: The global position encoding Pi of the target node vi is [0.15, 0.62], derived from Laplacian eigenvectors. This indicates the node has a strong presence in the central area of the graph rather than at the periphery. Its node influence Ci is 0.78 (computed via decay-jump propagation), indicating moderate to high influence. This pattern is quite common in neural network research papers, especially in the Cora citation network, where neural network papers tend to form larger connected communities and have higher citation influence.

Expert A (Local Feature Analysis) Step 2: Analyzing deeper patterns in the feature vector, I notice that besides terms related to "neural" and "network," there may also be high values for terms related to deep learning, activation functions, or weights. This combination of vocabulary is very typical in neural network literature. The lack of high-frequency vocabulary related to rule learning, case reasoning, or probabilistic methods further supports the neural network classification hypothesis. The pattern of the feature vector highly aligns with the characteristics of known neural network papers in the Cora dataset.

Expert B (Neighborhood Structure Analysis) Step 2: Further examining the topological environment of node vi, the key subgraph structure of 4 nodes and 6 edges indicates a highly interconnected small community. In citation networks, papers on similar topics tend to cite each other, forming such tight structures. Considering the structural role represented by hash value 0xB4E1, I infer that vi and its neighbors likely belong to the same research sub-domain. By comparing with typical connection patterns of different categories of papers in the Cora dataset, this structure best matches the characteristics of Neural_Networks category papers, which typically form denser citation clusters.

Expert C (Global Position Analysis) Step 3: Combining global position and influence analysis, the characteristics of node vi highly match the Neural_Networks category. In the Cora dataset, neural network research papers often occupy central positions (consistent with Pi=[0.15, 0.62]) and have higher influence scores (Ci=0.78). Other categories such as Theory typically appear at peripheral positions in the graph, while Rule_Learning papers tend to have lower connectivity. Based on global position and influence analysis, I predict this node belongs to the Neural_Networks category, with a confidence of 0.85.

Expert A (Local Feature Analysis) Step 3: Based on vocabulary feature analysis, and referencing known category feature patterns in the Cora dataset, I can definitively exclude Case_Based, Genetic_Algorithms, Rule_Learning, and Theory categories, as the feature vector lacks characteristic words for these domains. Among the remaining categories, Neural_Networks has the highest match, followed by Probabilistic_Methods, with Reinforcement_Learning being the lowest. My final prediction is the Neural_Networks category, with a confidence of 0.92.

Expert B (Neighborhood Structure Analysis) Step 3: Through topological structure analysis, combined with the structural role represented by the WL hash value, I confirm that the structure formed by node vi and its neighbors in the Cora dataset most closely aligns with the Neural_Networks category. This structure does not match the typical connection patterns of Theory or Probabilistic_Methods papers, which usually have different citation behaviors. Based on the node's connection structure and neighbor features, I predict this node belongs to the Neural_Networks category, with a confidence of 0.88.

Integrated Analysis:
All three experts analyzed the target node vi from different perspectives, all pointing to the Neural_Networks category:
- Expert A, through local vocabulary feature analysis, found that high-frequency vocabulary is highly related to neural network research, with a confidence of 0.92
- Expert B, through neighbor topological structure analysis, found that the dense connection pattern matches the characteristics of neural network papers, with a confidence of 0.88
- Expert C, through global position and influence analysis, confirmed that the node's centrality and influence are consistent with neural network papers, with a confidence of 0.85

All experts unanimously support the Neural_Networks classification, with no expert raising objections or leaving the discussion, indicating consistency across all reasoning paths. The analyses from three different perspectives mutually validate each other, enhancing the reliability of the prediction.

Final Prediction: Neural_Networks
Overall Confidence: 0.89
Confidence Calculation Method: Weighted average of the three experts' confidence scores, with weights based on the comprehensiveness and evidence strength of each expert's analysis (0.92*0.35 + 0.88*0.35 + 0.85*0.30 = 0.89)

Figure 15. Expert Collaboration ToT's GPT-4 answer with Cora dataset.

Expert Collaboration ToT (ANSWER)

Expert A (Local Feature Analysis) Step 1: I'll first analyze the local feature vector Si of the target node vi. This is a 1,433-dimensional vector representing word occurrences in the paper. I notice that dimensions related to "neural" and "network" have relatively high values (such as [...0.3...]), which may indicate that this paper is related to neural networks. However, I also observe that dimensions related to "probability", "bayesian", and "likelihood" also have certain values, which might suggest elements of probabilistic methods.

Expert B (Neighborhood Structure Analysis) Step 1: Looking at the neighborhood structure of node vi, it is directly connected to nodes vj, vk, and vm. The structural role Ri with hash value 0xB4E1 (after 3 WL iterations) indicates that this node exists in a dense connection pattern. The key subgraph shows an average degree of 3.0, indicating this is a relatively tight citation cluster. Such structures may appear in multiple research domains, requiring further analysis to determine the specific category.

Expert C (Global Position Analysis) Step 1: The global position encoding Pi of the target node vi is [0.15, 0.62], indicating the node has a strong presence in the central area of the graph. Its node influence Ci is 0.78, indicating moderate to high influence. This pattern may appear in core papers across multiple research domains, including neural networks, probabilistic methods, or reinforcement learning and other popular fields. More information is needed to narrow down the possible categories.

Expert A (Local Feature Analysis) Step 2: Analyzing the feature vector more deeply, I find that despite terms related to neural networks, the frequency of terms like "bayesian", "distribution", and "likelihood" related to probabilistic methods is higher. I also notice significant occurrences of reinforcement learning terms such as "reinforcement", "reward", and "policy". This makes me doubt my preliminary judgment about neural networks. Now it appears that the paper might be related to probabilistic methods or reinforcement learning, or a combination of both.

Expert B (Neighborhood Structure Analysis) Step 2: Further examining the features of node vi's neighbors, I notice that the feature vectors of neighbor nodes vj and vk contain many terms related to probabilistic methods, while vm contains more reinforcement learning terms. This mixed pattern suggests that the paper may be in the intersection of probabilistic methods and reinforcement learning. Considering typical citation patterns in the Cora dataset, this structure most likely corresponds to reinforcement learning papers, especially those that use probabilistic methods.

Expert C (Global Position Analysis) Step 2: Analyzing the node's position in the entire graph, I find it is positioned at the connection between two communities—one mainly composed of probabilistic methods papers and the other mainly of reinforcement learning papers. This "bridging" position is typically occupied by interdisciplinary research papers. The global influence score of 0.78 also supports this view, indicating that the paper has influence across multiple research communities.

Expert A (Local Feature Analysis) Step 3: ***[PRUNING/WITHDRAWAL]*** "***I notice that my analysis path may contain contradictions. Initially, I leaned towards neural network classification, then considered probabilistic methods or reinforcement learning. After re-examining the feature vector, I find that the keyword pattern shows terms like "reinforcement", "reward", "policy", "learning", and "state" are significantly higher than terms related to other categories. My previous analysis was not systematic enough and may have misled the reasoning. Due to my inability to provide consistent high-confidence analysis, I choose to withdraw from the discussion.***"

Expert B (Neighborhood Structure Analysis) Step 3: Based on comprehensive analysis of topological structure and neighbor features, as well as the structural pattern represented by the WL hash value, I confirm that this node most likely belongs to the Reinforcement_Learning category. This conclusion is based on: 1) the significant presence of reinforcement learning terms in neighbor node features; 2) its structural position connecting probabilistic methods and machine learning communities; 3) similarity to the topological structure of known reinforcement learning papers in the Cora dataset. My final prediction is the Reinforcement_Learning category, with a confidence of 0.83.

Expert C (Global Position Analysis) Step 3: Based on the node's global position, influence analysis, and bridging characteristics, combined with the typical position distribution of different research domains in the Cora dataset, I believe this node most likely belongs to the Reinforcement_Learning category. Reinforcement learning papers typically have this characteristic of connecting different research communities, especially connecting probabilistic methods and machine learning communities. My final prediction is the Reinforcement_Learning category, with a confidence of 0.79.

Integrated Analysis:
In this analysis, Expert A realized in step 3 that their analysis contained contradictions and could not provide consistent high-confidence judgment, therefore chose to withdraw from the discussion. Experts B and C consistently support the Reinforcement_Learning category from different perspectives:
- Expert B, through neighbor structure and topological feature analysis, arrived at a confidence of 0.83
- Expert C, through global position and bridging characteristic analysis, arrived at a confidence of 0.79

The two remaining experts unanimously believe that this node belongs to the Reinforcement_Learning category, with clear and consistent reasoning logic and no obvious contradictions.

Final Prediction: Reinforcement_Learning
Overall Confidence: 0.81
Confidence Calculation Method: Weighted average of the two remaining experts' confidence scores, with weights based on the comprehensiveness and evidence strength of each analysis (0.83*0.55 + 0.79*0.45 = 0.81). Expert A's analysis was pruned and not included in the final decision.

Figure 16. Expert Collaboration ToT's GPT-4 answer with Cora dataset (pruning).