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GMCoT: a graph-augmented multimodal chain-of-thought reasoning framework for multi-label zero-shot learning

Key words: Chain-of-thought; Multi-label zero-shot learning; Multimodal reasoning; Large language model

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Motivation

The Problem: Multi-Label Zero-Shot Learning (ML-ZSL)

- Task: Assigning multiple labels to an image (e.g., "sky", "sea", and "ship") where some labels (unseen classes) never appear during training.
- Difference from standard classification: Requiring the prediction of a set of labels rather than a single class, which can generalize to completely new concepts.

Key Challenges:

- Semantic Gap: Difficulty in effectively transferring knowledge between different modalities (visual features vs. textual semantics).
- Complex Label Correlations: Labels in the real world are highly correlated (e.g., "car" and "road" co-occur). Standard binary relevance methods fail to model these dependencies.

Limitations of Existing Methods:

- Often rely on single-modal knowledge.
- Lack visual grounding for unseen concepts.
- Do not utilize structured reasoning (human-like inference).

Main idea: GMCoT Framework

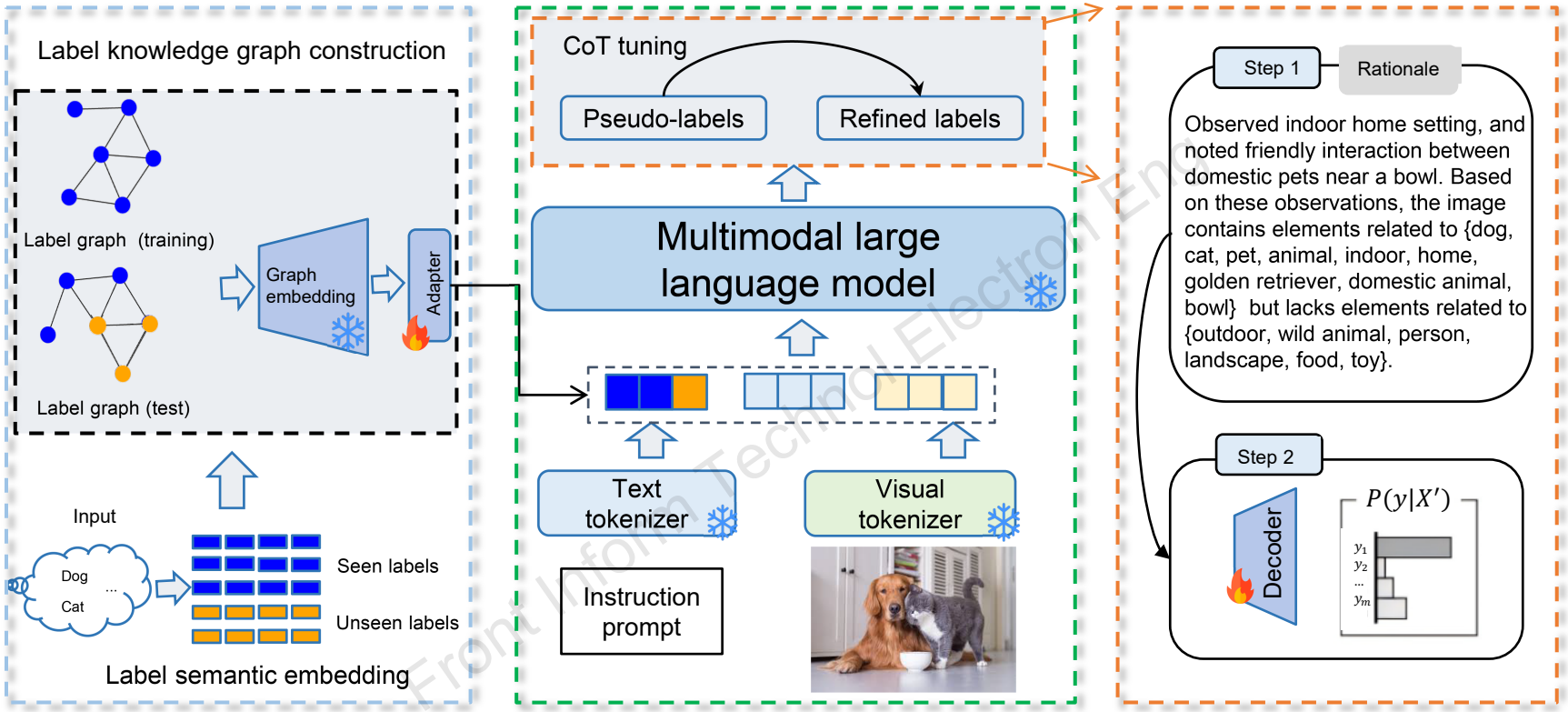
Core Innovation:

- GMCoT (Graph-augmented Multimodal Chain-of-Thought): A novel framework that combines valid multimodal Large Language Models (MLLMs) with graph-based structured knowledge.

Key Approaches:

- Human-like Reasoning: Imitates step-by-step reasoning (Chain-of-Thought) to decompose complex visual recognition into intermediate observations and final conclusions.
- Graph Augmentation: Explicitly integrates a Label Knowledge Graph to capture semantic relationships between seen and unseen labels.
- Synergy: Leverages the generative power of LLMs while constraining and guiding predictions using structured graph embeddings.

Framework



Two-Stage Graph-Augmented Framework

Built on Mono-InternVL with lightweight adapters, our approach fuses graph embeddings in a two-stage pipeline. It first generates natural language rationales to interpret visual content, and then utilizes these rationales to predict final labels, enabling robust zero-shot classification with high parameter efficiency.

Method: Label Knowledge Graph

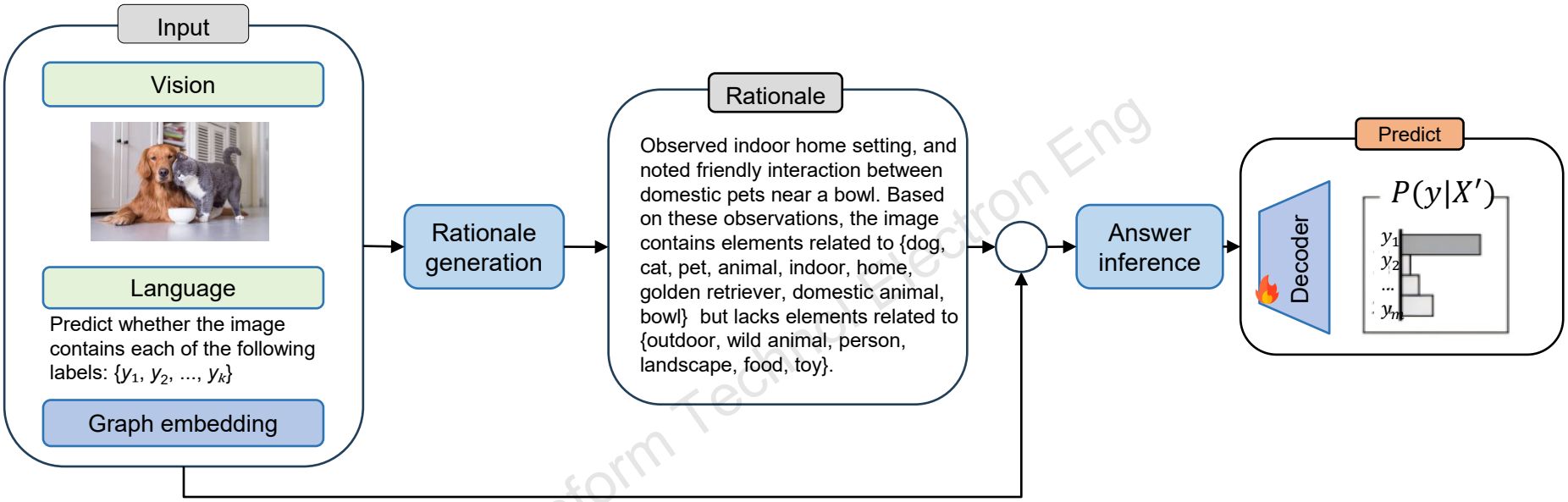
Construction:

- Nodes: Represent all labels (Set $C = S \cup U$), where S represents seen labels and U unseen labels.
- Embeddings: Initialized using the CLIP text encoder to ensure visual-semantic alignment.
- Graph Neural Network (GCN): Refines embeddings to capture structural relationships.

Augmentation Strategy:

- Edges: Created based on semantic relations.
- Enhancement: Additional edges are added based on pairwise cosine similarity ($> \epsilon$) between label embeddings.
- Purpose: Enables effective information propagation from seen classes (training) to unseen classes (inference), bridging the zero-shot gap.

Method: Graph-Augmented CoT



1. Input Fusion: The model integrates visual and textual features with structured graph embeddings to capture semantic correlations between seen and unseen labels.

2. Two-Stage Reasoning: It employs a Chain-of-Thought pipeline that first generates natural language rationales to bridge the semantic gap, guiding more accurate final predictions.

Experimental Setup

Datasets:

1. NUS-WIDE:
   - Training: 925 user-generated tags (Seen).
   - Testing: 81 human-verified concept labels (Unseen).
2. Open Images (V4):
   - A more challenging, large-scale dataset.
   - Training: 7186 labels.
   - Testing: Top 400 frequent labels not present in training.

Evaluation Protocols:

- Zero-Shot Learning (ZSL): Train on seen; evaluate only on unseen.
- Generalized ZSL (GZSL): Train on seen; evaluate on both seen and unseen (more realistic).

Metrics:

- Mean Average Precision (mAP)
- F1-score at Top-*K* (F1@*K*)

Major results

Table 1 ZSL results obtained on the NUS-WIDE dataset. Performance is measured in terms of precision (P), recall (R), and F1-score at $K=3,5$, and mean average precision (mAP), all in %

Method	P@3	R@3	F1@3	P@5	R@5	F1@5	mAP
LESA (M=10)	25.7	41.1	31.6	19.7	52.5	28.7	19.4
ZS-SDL	24.2	41.3	30.5	18.8	53.4	27.8	25.9
BiAM	26.6	42.5	32.7	20.5	54.6	29.8	25.9
ML-Decoder	28.2	43.2	34.1	22.3	55.1	30.8	31.1
CLIP-Decoder	28.6	43.5	34.8	**22.7**	55.5	31.1	33.4
MKT	27.7	44.3	34.1	21.4	57.0	31.1	37.6
Qwen-2.5-VL (prompting)	28.1	44.8	34.8	22.5	57.2	32.3	38.8
GMCoT	**28.7**	**45.5**	**35.2**	**22.7**	**57.8**	**32.6**	**39.4**

The best results are in bold

Table 2 ZSL results obtained on the Open Images dataset. Performance is measured in terms of precision (P), recall (R), and F1-score at $K=10,20$, and mean average precision (mAP), all in %

Method	P@10	R@10	F1@10	P@20	R@20	F1@20	mAP
LESA (M=10)	0.7	25.6	1.4	0.5	37.4	1.0	41.7
ZS-SDL	6.1	47.0	10.7	4.4	68.1	8.3	62.9
BiAM	3.9	30.7	7.0	2.7	41.9	5.5	65.6
ML-Decoder	9.2	82.8	17.5	6.4	90.7	10.4	64.8
CLIP-Decoder	11.1	85.3	20.1	6.2	93.3	12.1	67.3
MKT	11.1	86.8	19.7	6.1	94.7	11.4	68.1
Qwen-2.5-VL (prompting)	11.2	87.2	20.2	6.8	94.1	12.2	68.9
GMCoT	**11.9**	**88.5**	**20.8**	**7.1**	**95.8**	**12.5**	**69.6**

The best results are in bold

Major results

Table 3 GZSL results obtained on the NUS-WIDE dataset. Performance is measured in terms of precision (P), recall (R), and F1-score at $K=3,5$, and mean average precision (mAP), all in %

Method	P@3	R@3	F1@3	P@5	R@5	F1@5	mAP
LESA (M=10)	23.6	10.4	14.4	19.8	14.6	16.8	5.6
ZS-SDL	27.7	13.9	18.5	23.0	19.3	21.0	12.1
BiAM	25.2	11.1	15.4	21.6	15.9	18.2	9.4
ML-Decoder	27.1	17.6	23.3	21.1	23.2	26.1	19.9
CLIP-Decoder	27.4	18.3	24.8	22.2	23.7	27.5	23.8
MKT	35.9	15.8	22.0	29.9	22.0	25.4	18.3
Qwen-2.5-VL (prompting)	36.1	16.5	22.2	30.1	22.9	25.7	24.5
GMCoT	**36.7**	**19.2**	**26.3**	**30.9**	**24.2**	**28.1**	**25.2**

The best results are in bold

Table 4 GZSL results obtained on the Open Images dataset. Performance is measured in terms of precision (P), recall (R), and F1-score at $K=10,20$, and mean average precision (mAP), all in %

Method	P@10	R@10	F1@10	P@20	R@20	F1@20	mAP
LESA (M=10)	16.2	18.9	17.4	10.2	23.9	14.3	45.4
ZS-SDL	35.3	40.8	37.8	23.6	54.5	32.9	75.3
BiAM	13.8	15.9	14.8	9.7	22.3	14.8	81.7
ML-Decoder	35.8	41.7	38.8	23.7	56.4	34.1	75.4
CLIP-Decoder	38.2	44.5	41.1	26.2	**59.3**	36.3	78.2
MKT	37.8	43.6	40.5	25.4	58.5	35.4	81.4
Qwen-2.5-VL (prompting)	38.4	44.6	41.3	26.4	58.8	36.3	82.1
GMCoT	**38.7**	**45.1**	**42.7**	**26.6**	59.2	**36.4**	**82.5**

The best results are in bold

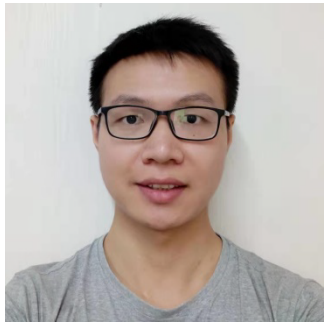
Conclusions

Summary:

- Framework: Proposed GMCoT, a reasoning framework acting as a bridge between visual perception and logical label inference.
- Integration: Successfully integrated Label Knowledge Graphs with Multimodal Chain-of-Thought reasoning.
- Outcome: State-of-the-Art (SOTA) results on standard benchmarks (NUS-WIDE and Open Images).

Impact:

- The approach mimics human cognitive processes (Observe → Reason → Conclude).
- Explicit capturing of label co-occurrences improves consistency in multi-label predictions.
- Proven effectiveness for handling "unseen" concepts in dynamic real-world applications (e.g., image annotation).



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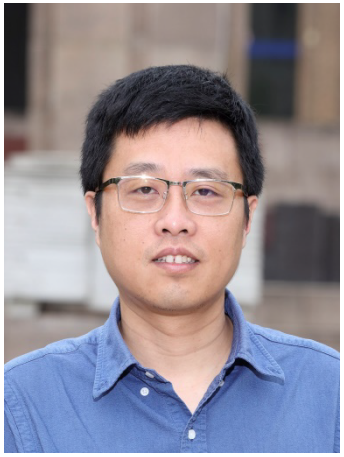

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