UNICOTT: A UNIFIED FRAMEWORK FOR STRUCTURAL CHAIN-OF-THOUGHT DISTILLATION

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Introduction

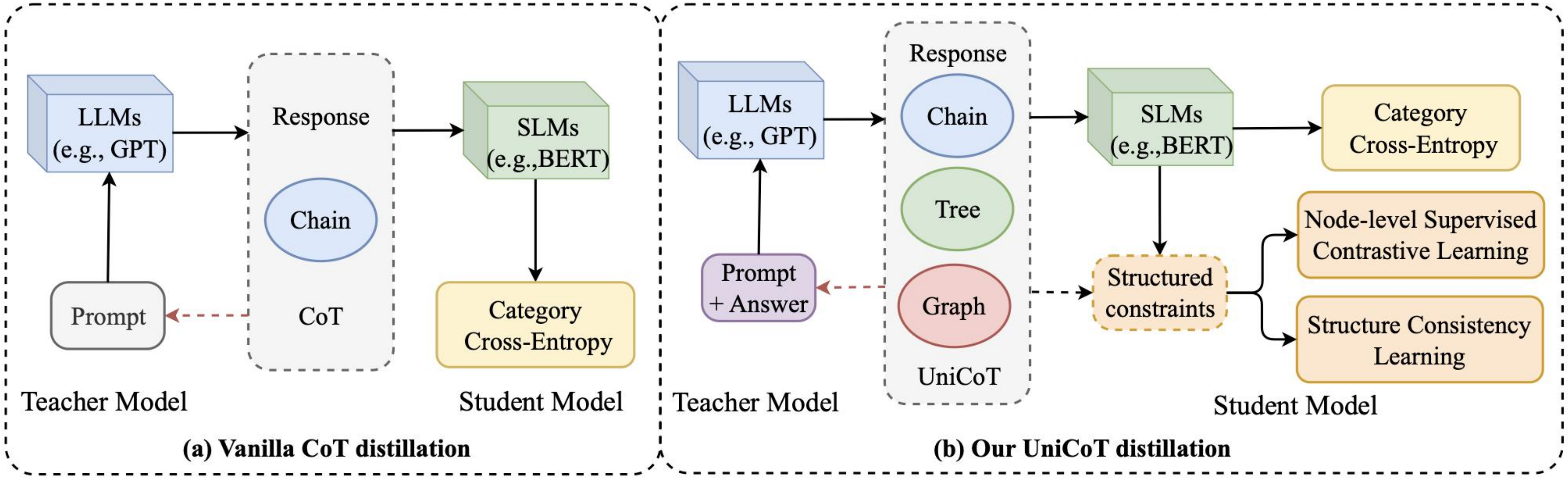


Figure 1: We compare different architectures: (a) generating vanilla CoT for distillation; (b) our UniCoTT, which uses UniCoT as a bridge to transfer knowledge between diverse structural thoughts.

Motivation

- How to efficiently transfer the CoT capabilities that LLMs possess to SLMs while preventing LLMs from producing erroneous reasoning explanations that could degrade performance.
- How to uniformly consider CoT prompts with different structures, such as chain, tree, and graph structures, in the process of knowledge transfer (i.e., prompting LLMs and training SLMs).

Contribution

- UniCoTT prompts LLMs to construct **precise structured CoTs** (i.e., UniCoT) in a unified way.
- UniCoTT utilizes the proposed **unified supervised learning** and **structural consistency learning** strategies to transfer knowledge of structured CoT to SLMs.

Methods

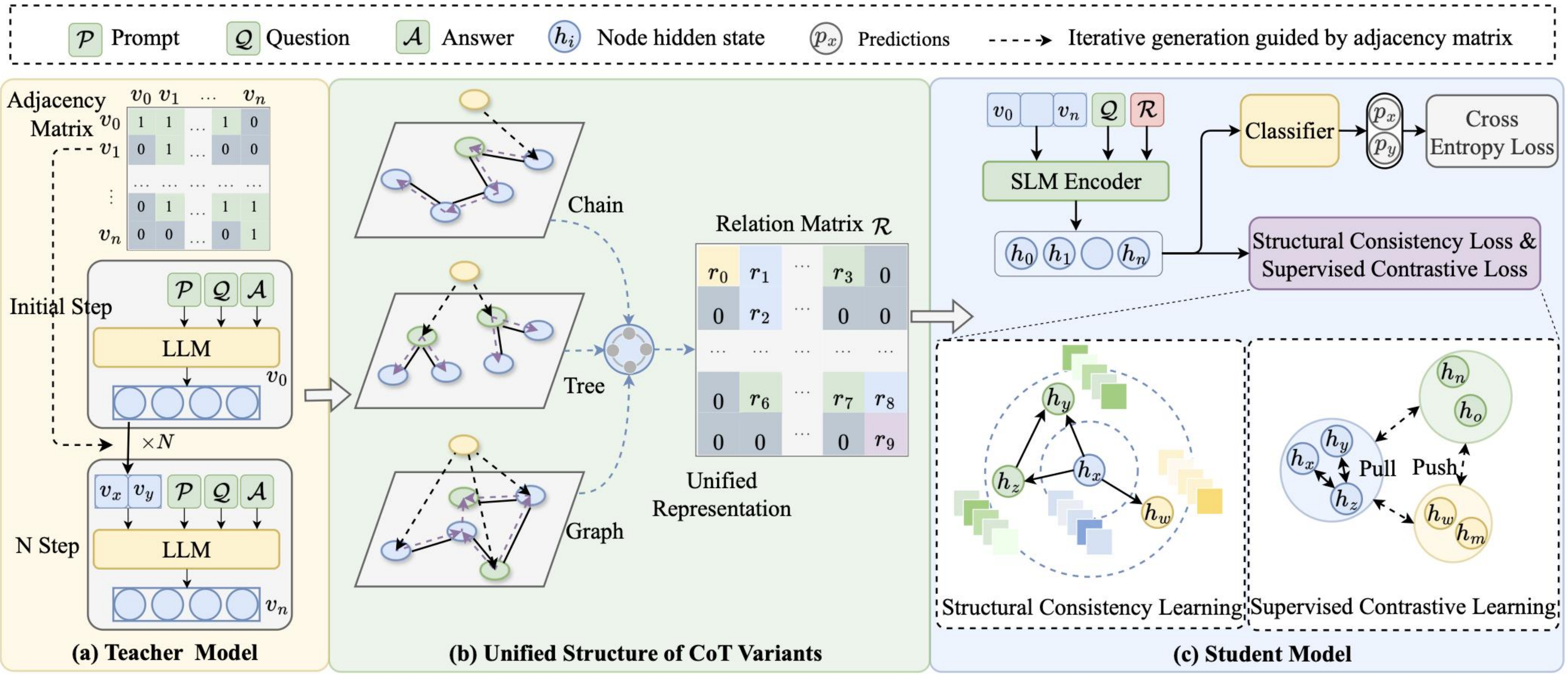


Figure 2: The illustration of our method, consisting of (1) LLMs construct UniCoT consisting of explanations with structural logic through N-step iteration; (2) SLMs obtain structured knowledge in UniCoT through node-level supervised contrastive loss and structural consistency learning.

Overview of UNICoTT

Teacher Network

$$v_i{}^* = \arg\max \log P\left(v_i \mid p, q, a^*, \mathcal{P}(v_i)\right)$$

Student Network

$$\mathcal{L}_{cce}(y) = \sum_i a_i^* \log(\hat{y}_i)$$

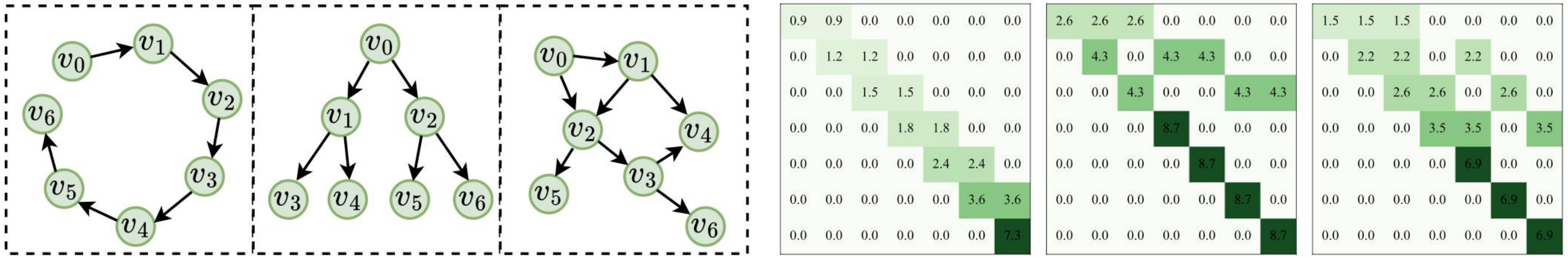
Construction of UNICoT

Iteratively Constructing UniCoT

$$v_t \sim p_{\mathrm{LLM}}(v_t | p, q, a^*, \mathcal{P}(v_t))$$

Unified Representation of UniCoT

$$r_{ij} = \frac{a_{ij}}{\mathrm{Dij}(v_i, \phi(v_i))}$$



Node-level supervised contrastive loss

$$h_j = \mathrm{Encoder}_{\mathrm{SLM}}(v_j), \quad \forall j \in \{0, \ldots, N_v\},$$

$$\mathcal{L}_{\mathrm{nsc}} = - \sum_{j,j'=0, j!=j'}^{N_v} \log \frac{\exp(v_j \cdot v_{j'}/\tau)}{\sum_{k=1}^{K} \exp(v_j \cdot v_k^n/\tau)},$$

Structural consistency learning

$$\xi_\chi = \sum_i^{N_v} \|\mathbf{W} \cdot s_i - \chi_i\|$$

$$\mathcal{L}_{sd} = \frac{1}{D} \sum_{d=1}^{D} \mathrm{ReLU}\left(1 - \sqrt{\sigma_d + \tau_{sd}}\right)$$

$$\mathcal{L}_{se} = \frac{1}{D \times (N_v - 1)} \sum_{i!=j} \Sigma_S[i, j].$$

Experiment

Table 1: A performance comparison of various methods on the factual reasoning benchmark, with the best results emphasized in **bold**. The Base Model is the student network used for training. The results of using more pre-training language models as the base model are provided in Appendix A.4.

Base Model	Method	Structure	CREAK			CSQA2			StrategyQA		
			Acc.	F1.	Ins.	Acc.	F1.	Ins.	Acc.	F1.	Ins.
BERT-base	+None	-	69.3	69.1	70.1	55.1	55.0	55.4	82.7	82.7	82.3
	CoT	Chain	77.7	76.6	78.7	71.1	71.0	70.9	87.7	87.6	88.4
	SCOTT	Chain	84.1	84.2	83.5	85.2	85.2	86.6	90.0	89.8	90.8
	DSbS	Chain	69.5	69.5	69.4	54.2	54.1	54.9	81.0	80.9	80.7
	UniCoTT	Chain	92.7	92.8	93.0	81.5	81.4	81.8	90.9	90.9	91.1
	UniCoTT	Tree	94.5	94.4	94.9	**87.9**	**87.9**	**89.2**	**93.4**	**93.5**	**94.0**
	UniCoTT	Graph	**95.8**	**95.6**	**96.0**	83.8	83.4	84.9	92.1	92.4	93.2
RoBERTa-base	+None	-	71.3	71.3	71.4	56.0	55.8	55.7	83.9	83.9	84.1
	CoT	Chain	86.5	86.4	86.7	72.7	72.6	72.4	86.6	86.5	90.0
	SCOTT	Chain	90.2	90.2	90.5	82.3	82.3	81.6	91.5	91.2	90.9
	DSbS	Chain	72.2	72.2	72.4	54.2	54.0	55.3	80.0	80.0	80.2
	UniCoTT	Chain	93.4	93.4	93.3	82.2	82.6	82.0	93.6	93.4	94.4
	UniCoTT	Tree	94.8	94.6	94.7	**88.8**	**88.9**	**90.2**	**94.6**	**94.6**	**95.5**
	UniCoTT	Graph	**96.8**	**96.8**	**95.9**	84.9	84.6	85.9	94.2	93.9	94.7

Experiment

Table 2: A performance comparison of various methods on the Multiple-Choice QA benchmark, with the best results emphasized in **bold**. The Base Model is the student network used for training. The results of using more pre-training language models as the base model are provided in Appendix A.4.

Base Model	Method	Structure	CSQA			OBQA			QASC		
			Acc.	F1	Ins.	Acc.	F1.	Ins.	Acc.	F1.	Ins.
BERT-base	+None	-	81.6	68.6	57.4	75.9	65.7	52.8	84.8	55.8	24.2
	CoT	Chain	86.7	77.0	71.1	77.5	69.0	61.4	89.3	73.6	57.0
	SCOTT	Chain	88.7	80.2	77.3	80.8	71.0	64.4	86.4	64.5	53.8
	DSbS	Chain	81.3	68.2	56.2	76.4	63.2	52.0	87.1	54.5	22.8
	UniCoTT	Chain	88.1	80.9	79.2	82.4	75.8	73.6	92.3	81.1	70.3
	UniCoTT	Tree	90.4	84.9	84.4	83.8	75.6	75.2	**93.2**	**83.3**	**77.8**
	UniCoTT	Graph	**91.6**	**88.0**	**86.8**	**84.4**	**77.9**	**77.2**	90.3	83.6	68.5
RoBERTa-base	+None	-	83.3	72.6	64.4	78.4	69.5	61.4	86.7	58.5	32.3
	CoT	Chain	86.7	77.7	71.0	84.4	78.3	74.4	90.9	75.4	60.3
	SCOTT	Chain	89.8	83.7	78.9	84.8	77.9	73.0	87.5	60.4	30.8
	DSbS	Chain	82.8	72.4	64.3	77.6	69.0	60.0	87.5	59.7	34.6
	UniCoTT	Chain	91.7	86.5	86.7	84.3	79.2	78.7	92.9	84.6	78.6
	UniCoTT	Tree	91.7	86.9	87.5	87.5	83.4	82.2	**93.6**	**84.5**	**80.1**
	UniCoTT	Graph	**92.5**	**89.6**	**88.8**	**88.8**	**85.4**	**84.1**	92.4	83.7	75.7

Experiment

Table 3: A performance comparison on the GLUE benchmark, with the best results emphasized in **bold**. I and II indicates using BERT-base and RoBERTa-base as the base model, respectively.

Base Model	Methods	Structure	CoLA	RTE	WNLI	MRPC	**Average.**
BERT-base	+None	-	56.6	65.3	53.4	81.8	64.3
	CoT	Chain	67.9	81.6	80.3	87.8	79.4
	SCOTT	Chain	81.1	91.7	91.6	92.6	89.3
	UniCoTT	Chain	86.4	89.9	93.0	95.5	91.2
	UniCoTT	Tree	88.5	93.5	**94.4**	**96.3**	**93.2**
	UniCoTT	Graph	**90.2**	**94.6**	93.9	94.1	**93.2**
RoBERTa-base	+None	-	56.7	78.7	55.5	86.9	69.5
	CoT	Chain	69.6	82.3	81.2	71.3	76.1
	SCOTT	Chain	78.5	89.9	90.8	90.6	87.5
	UniCoTT	Chain	88.3	91.7	93.4	93.1	91.6
	UniCoTT	Tree	91.4	93.0	95.1	**96.3**	94.0
	UniCoTT	Graph	**93.9**	**95.5**	**95.3**	94.0	**94.7**

Conclusion

In this paper, we :

- Present a unified distillation framework, UniCoTT, designed for CoT with diverse reasoning structures.
- Propose an efficient method for generating CoT with diverse structures and its unified representation approach.
- Introduce a node-level supervised contrastive loss and structural consistency learning strategy, aimed at facilitating supervised learning and representa- tion learning for structural knowledge transfer, respectively.
- Derive an upper bound for the structural representation error and achieve structural constraints by optimizing this upper bound.
- The experimental results show that UniCoTT can effectively improve the performance of SLMs on factual reasoning, multiple-choice QA, and NLU tasks.

Thank you!
Q&A