Making Language Model a Hierarchical Classifier and Generator

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Abstract

Decoder-only language models, such as GPT and LLaMA, generally decode on the last layer. Motivated by human's hierarchical thinking capability, we propose that a hierarchical decoder architecture could be built with different layers decoding texts simultaneously. Due to limited time and computationally resources, we choose to adapt a pretrained language model into this form of hierarchical decoder. Language heads of the last layer are copied to different selected intermediate layers, and fine-tuned with different task inputs. By thorough experiments, we validate that these selective intermediate layers could be adapted to speak meaningful and reasonable contents, and this paradigm of hierarchical decoder can obtain state-of-the-art performances on multiple tasks such as hierarchical text classification, classification-guided generation, and hierarchical text generation. HdLM outperforms all baselines on WoS, DBpedia, EScony, EmpatheticDialogues, and several cognitive tests. We also provide thorough theoretical analysis to validate the convergence and computational savings of our methodology. This study suggests the possibility of a generalized hierarchical reasoner, pretraining from scratch.

1 Introduction

Modern Large language models (LLM), such as GPT [1] and Llama [2], have made remarkable progresses on natural language tasks [3]. Based on the decoder-only architecture, such language models exhibit impressive generalizability and scalability on different tasks and scenarios. Among these tasks, textual reasoning is always challenged which often requires the model to explicitly plan the immediate steps and bootstrap the long-term rewards. To enhance such capabilities, chain-of-thought (CoT) [4] and corresponding finetuned or test-time scaling methods [5; 6; 7] are proposed, with the thought formulated either on the token-space or the latent-space.

However, these reasoning LLMs do not have an explicit hierarchical thinking mechanism, therefore might suffer from suboptimal solutions on complex reasoning tasks [8]. Their reasoning capabilities are constrained from the scale of annotated data, and the test-time scaling might be upper-bounded [9]. On the other hand, mankind is naturally empowered with hierarchical thinking capabilities [8], typically in two aspects:

- (i) Different abstraction of conceptual levels: the coarse-grained, strategic decisions guide the generation of fine-grained, detailed decisions.
- (ii) Sequential determination: a key determination is first selected from available options while subsequent options are subject to the selection.

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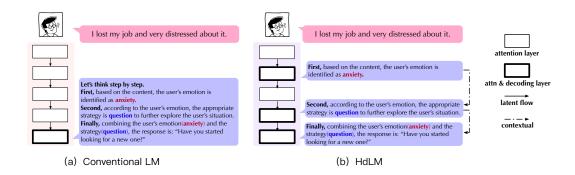


Figure 1: Paradigm of HdLM compared to a conventional decoder-only language model. In contrast to the last layer decoding, HdLM employs different layers to decode different levels of texts.

Motivated from these hierarchical thinking mechanisms, models with automatic hierarchical thinking should be explored. Similar studies were mainly based on encoder-decoder architectures and may be classified into model-wise, scale-wise and layer-wise prototypes [10].

In this paper, we propose a new type of decoder called Hierarchical decoding Language model (HdLM), combining the model-wise and layer-wise prototypes. We inherit the strong semantic understanding and generation capabilities of modern LLM, but allow its multiple layers to decode plausible textual contents. An earlier layer may produce more prerequisite, coarse-grained expressions which also work for the context of resulted, fine-grained expressions, which are decoded by later layers (Figure 1). Such type a language model can automatically produce reasonable performance on sequential pipelines of classification and generation tasks, which are verified by our substantial experiments. Comparing with the conventional reasoning LLM, HdLM also enjoys computational savings for both training and inference, which are both verified by theoretical derivation and empirical observations. Our code and model can be found on https://github.com/coswindywang/HdLM. Our main contributions can be summarized as follows:

- (1) We propose HdLM, which can deal with different types of hierarchical tasks, including hierarchical text classification, classification-guided generation, and hierarchical text generation.
- (2) We provide a theoretical analysis on the computational benefit HdLM, and also a discussion on its convergence.
- (3) We conduct substantial experiments and corresponding analysis to verify HdLM's performance, on both classification and generation metrics, as well as its out-of-domain generalization capability.
- (4) We discuss about its connection with alternative solutions such as vanilla SFT, cascade, multi-hop, and its scalability and the possibility of an end-to-end framework.

2 Method

In this section, we first formalize the problem, then propose a dual-layer fine-tuning mechanism, and finally a two-pass inference paradigm.

2.1 Problem Formulation

Given a language model $i\mathcal{M}$, its total number of layers is K, and the language head is \mathcal{H} . Different from traditional query-response tasks, here we try to define a generalized hierarchical textual tasks. Given a user query q, hierarchical textual tasks requires the agent to generate a sequence of responses $\mathbf{r}_{1:D} := \{r_1, r_2, \cdots, r_D\}$, in which D is the hierarchical depth. The standard format of hierarchical textual data then becomes $(q, \mathbf{r}_{1:D})$. We use L and L_d to denote the lengths of q and r_d , respectively.

The above hierarchical textual task can be solved recursively. That is, for each step $i \in \{1, 2, \dots, D\}$, the current response can be produced grounded by the query and prior responses:

$$\mathcal{T}_i \in \{\mathcal{C}, \mathcal{G}\} : r_i \leftarrow \mathcal{M}(q, \mathbf{r}_{1:i-1}) \tag{1}$$

where \mathcal{T} denotes a uni-step subtask. Here we further argue \mathcal{T} can be generally classified into two categories: the classification task \mathcal{C} and the generation task \mathcal{G} . As indicated in Figure 2, the following different paradigms can be summarized from hierarchical textual tasks:

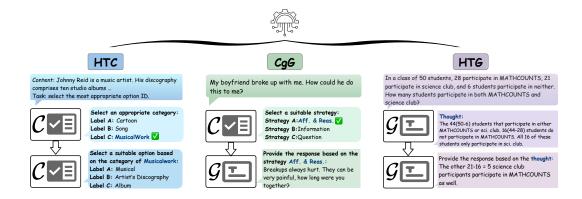


Figure 2: Typical paradigms (hierarchical text classification, classification-guided generation, hierarchical text generation) of hierarchical text tasks. C denotes classification and G denotes generation.

Hierarchical text classification (HTC): classifications are asked from the coarse-grained label to the fine-grained label. The lower-level label candidates are usually constrained by the choice of the higher-level label. We denote this paradigm as $C \to C$.

Classification-guided generation (CgG): a classification result is first required, then the final response is generated based on that classified label. This paradigm can be denoted as $C \to G$.

Hierarchical text generation (HTG): the final response is posterior inferenced by intermediate generations, such as the chain of thought, reasoning, or thoughts. This paradigm is denoted as $\mathcal{G} \to \mathcal{G}$.

Other hierarchical tasks: there might be even more completed hierarchical tasks. For example, the generative classification $(\mathcal{G} \to \mathcal{C})$ and 'think, classify and act' $(\mathcal{G} \to \mathcal{C} \to \mathcal{G})$. We leave these types of tasks for future works.

While there are evident methods to solve hierarchical textual tasks, either by computation time scaling (such as CoT or reasoning LLM), or the multi-hop inference, in this paper we propose a single-model framework which has less computational overheads.

2.2 Architecture

In this section, we propose an adjusted architecture based on the decoder-only transformer, which can also deal with hierarchical textual tasks by post-hoc adaptations. We first make a reasonable assumption that the depth of hierarchical textual task is smaller, i.e., D < K. Then we select D-1 intermediate layers with their indices satisfying:

$$k \in \{k_1, \cdots, k_{D-1}, K\}, 0 < k \le K$$
 (2)

These layers, along with the final layer, are used to decode D responses. To achieve this objective, we replicate the language heads in the K-th layer to the D-1 intermediate layers, with the parameter randomly initialized.

$$\mathcal{H}_d \leftarrow \mathcal{H}_K, d = 1, 2, \cdots, D - 1$$
 (3)

To make the derivation clearer, we propose some notations. Given a language model \mathcal{M} , \mathcal{M}_k represents its k-th layer. The forward pass from the k_1 to k_2 -th layer is denoted by $\mathcal{M}_{k_1:k_2}$, while $\mathcal{M}_{k_1:k_2}^{L_1}$ denotes the forward pass plus a textual generation.

The final layer still holds the standard supervised Fine-Tuning (FT) loss:

$$\mathcal{L}_{D}^{\text{FT}} = -\frac{1}{L_{D}} \sum_{j=1}^{L_{D}} \log \left[P(r_{D}(j)|q, \mathbf{r_{1:D-1}}, r_{D}(1:j-1)) \right]$$
 (4)

where j denotes the j-th token of r_D .

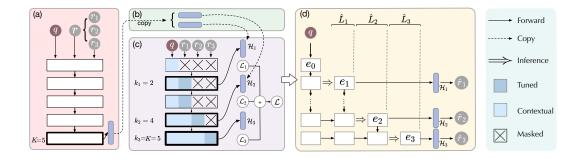


Figure 3: The pipeline of HdLM, with exampled D=3 and K=5. (a): A depth=3 hierarchical task on a conventional LM. (b): Replicate the language heads of the K-th layer to layer k_1, k_2 . (c): Training HdLM with the fine-tuning loss of r_d on the k_d -th layer. (d): Inference HdLM on the k_d -th layer sequentially with decoded \hat{r}_d and corresponding length \hat{L}_d .

2.3 Training

The D-1 intermediate layers can not decode reasonably with newly added heads. To educate them to decode proficient language, post-hoc adaptation is needed.

Given the hierarchical textual sample $(q, r_{0:d})$, the latent vector of each hierarchical level can be calculated recursively by the forward pass of each LM block:

$$e_1 = \mathcal{M}_{0:k_1}(q), \quad e_{d+1} = \mathcal{M}_{k_d:k_{d+1}}(e_d,r_d), \quad \mathcal{L}_d = \mathcal{L}^{\mathrm{FT}}(q,e_{1:d},r_{1:d}), \quad d=1,2,\cdots,D$$
 (5) with the finetuning loss \mathcal{L}_d implemented on each decoding layer. The final loss can then be the linear combination of them: $\mathcal{L} = \sum_{d=1}^{D-1} f_d \mathcal{L}_d + \mathcal{L}_D$ with the list of $\{f_1,\cdots,f_{D-1},1\}$ as the loss weights. During the training, we implement the causal mask for both prior tokens and subsequent responses. Figure 3 exhibits the detailed masking matrices for all decoding layers.

2.4 Inference

We keep a similar forward logic of inference to the training. For the query q, we still calculate its logits throughout all attention layers, similar with the conventional language model. For each k-th layer, the prior latent vector is employed to decode the k-th response, while the new decoded latent is also employed to forward pass the final layer, until the final response is decoded grounded by all previous latents.

$$e_1, \hat{L}_1 = \mathcal{M}_{0:k_1}^{\xrightarrow{L_1}}(q), \quad e_{d+1}, \hat{L}_{d+1} = \mathcal{M}_{k_d:k_{d+1}}^{\xrightarrow{L_d}}(e_d)$$
 (6)

$$\hat{r}_d = \mathcal{H}_{k_d}(e_d(L + \sum \hat{L}_{< d-1} :)), \quad d = 1, 2, \dots, D$$
 (7)

Note the above expression has a similar structure to the state-space model (SSM).

3 Theoretical analysis

This section theoretically analyzes the computation savings of HdLM compared to a conventional LLM. We then briefly discuss the training convergence of HdLM with the connection between the index of the first decoding layer and the task depth.

3.1 Computational complexity analysis

In this subsection, we compare the computation FLOPs of our HdLM with a standard LLM, and verify that HdLM results in both training and inference reduction. To make the formulation simple and clear, here we discuss the 2-depth hierarchical task, *i.e.*, D = 2.

Parameter definitions. The input sequence length L, the output sequence lengths L_1 and L_2 , the hidden dimension E, indexes of two decoding layers $k_1 < K$ and $k_2 = K$, and the expand ratio of FFN dimension is c. We use \mathcal{F} to denote the FLOPs.

Training FLOPs savings. We begin with the forward FLOPs of a standard transformer from Equation 20 derived in Appendix: $\mathcal{F}_{\text{train}} \to 3(8+4c)E^2KL^2$. The LLM baseline simply treats the input, level-1 output and level-2 output as a flat sequence, with all layers engaged:

$$\mathcal{F}_{\text{train}}^{\text{baseline}} \approx 3fK(L + L_1 + L_2)$$
 (8)

where we use f to represent the fixed coefficient $(8+4c)E^2$ for simplicity. One the other hand, the training FLOPs of HdLM can be expressed as

$$\mathcal{F}_{\text{train}}^{\text{HdLM}} \approx 3fk_1(L+L_1) + 3f(K-k_1)(L+L_1+L_2)$$
 (9)

The training FLOPs savings then becomes

$$\mathcal{F}_{\text{train}}^{\text{baseline}} - \mathcal{F}_{\text{train}}^{\text{HdLM}} \approx 3fk_1L_2 > 0$$
 (10)

Inference FLOPs savings. The inference FLops of LLM baseline can be expressed as

$$\mathcal{F}_{\text{infer}}^{\text{baseline}} = fK \sum_{i=1}^{L_1 + L_2} (L + j - 1) \tag{11}$$

from Equation 21 derived in Appendix. While for HdLM, the inference FLOPs becomes

$$\mathcal{F}_{\text{infer}}^{\text{HdLM}} = fk_1 \sum_{j=1}^{L_1} (L+j-1) + f(K-k_1) \sum_{j=1}^{L_2} (L+L_1+j-1)$$
 (12)

and it is easy to further prove $\mathcal{F}_{\text{infer}}^{\text{baseline}} - \mathcal{F}_{\text{infer}}^{\text{HdLM}} > 0$ (detailed derivation in Appendix).

3.2 Convergence of decoder with arbitrary layers

This subsection briefly discusses the convergence issue, *i.e.*, how can we ensure any implementation decoding layer (with the index of k_d), has enough depth to learn the target semantic hierarchy (with depth d)? Our derivation is mainly motivated by the Minimum number of layers Theorem proposed in [11]

Theorem 1. The last position in the sequence cannot retrieve the embedding vector x_D of the target token with K transformer layers if $K < \log_3(2D)$.

Due to the page limit, here we leave the detailed assumption in [11] and the connection between retrieval and classification in the Appendix. Based on its conclusion, here we prove our Corollary 2: **Corollary 2.** Assume Theorem 1 holds in C or G, then for any $d \leq D$, the first k_d layers of transformer can always learn the top d-depth task information.

Proof. Given the strict increasing, non-repeat integer sequence $\{k_d\}$ with $d \in \{1, 2, \cdots, D\}, k \in \{1, 2, \cdots, K\}, D \leq K$, it is obvious to have $k_d \geq d$. Since $3^d > 2d$ holds for d >= 1, then we have $k_d \geq d > \log_3 2d$, which contradicts the situation in Theorem 1.

Corollary 2 ensures the theoretical feasibility of our approach. In the next section, we also verify this conclusion from empirical results.

4 Experiment

In this section, we consider answering the following research questions: **RQ1:** If the training of HdLM can converge with an arbitrary setting of k? **RQ2:** Can HdLM perform well on different types of hierarchical textual tasks and outperform conventional baselines? **RQ3:** Can HdLM generalized well on out-of-domain hierarchical textual datasets? **RQ4:** How to determine the key parameters and different components of HdLM? **RQ5:** What is the connection of HdLM with previous standardized or test-time scaling baselines, such as reasoning, multi-hop, or cascade solutions?

To address these issues, we first list the datasets we use for different types of hierarchical tasks, then the experimental settings and evaluation metrics, and followed by the main results. We finally provide thorough discussion on the open-domain performance, the ablation and sensitivity studies, and the actual computational savings.

 $^{^{2}}$ Here we omit the batch size term B since different samples' computation within a batch is parallel.

4.1 Datasets

HTC ($\mathcal{C} \to \mathcal{C}$). We use the famous WoS [12] (with depth D=2) and DBpedia [13] (with depth D=3) as the training datasets. WoS are abstracts of published papers from Web of Science while DBpedia extracts structured information from Wikipedia.

 \mathbf{CgG} ($\mathcal{C} \to \mathcal{G}$). We employ the emotional support conversation (ESC) scenario, in which each turn of conversation is annotated with the user's emotion and the assistant's response strategy. The model needs to sequentially classify the user emotion or the response strategy to further enhance the response quality. We utilize ESconv [14] as both training and in-domain (ID) test sets. To further validate the response generation, EmpatheticDialogues [15] is employed as an out-of-domain (OOD) test set which lacks of the strategy annotation.

HTG $(\mathcal{G} \to \mathcal{G})$. Here we examine two typical famous theory-of-mind (ToM) tests, the Sally-Anne false belief experiment, and the Vignette-based Problem. These cognitive tests contain misleading or disturbing information and the agent needs to reason from the ego-centric perspective. In these scenarios, the response is the (thought, answer) pair with depth D=2. We train HdLM on the ToMI [16] and BigToM [17] benchmarks, while zero-shot evaluate the model on the Vignette-based test provided by [18].

4.2 Setting

Implementation Details. We conduct a post-hoc adaptation on the basis of Llama3-8B-Instruct [19], which has a total K=32 attention layers. During training, we use the AdamW optimizer with decay of 0.01 and the cosine scheduler. The training batch size is 16 and the sequence length is 2048. The experiment is running on LlamaFactory [20] with 32 A100 GPUs, lasting about 16 hours. Other settings, which is dataset-wise, are listed in the Appendix.

Classification metrics. F1-related scores including Micro-F1 and Macro-F1 are used. Micro-F1 considers the overall precision and recall of all instances, while Macro-F1 equals the average F1-score of labels. For CgG tasks, we also provide the classification accuracy, and the preference *bias* as defined by [21] based on Bradley-Terry model [22] ³. For HTC tasks, we provide the metric results on the bottom level of labels.

Generation metrics. We utilize the famous metrics of BLEU-2 (B-2), Rouge-L (R-L) and CIDEr. BLEU-2 (**B-2**)[23] first compute the geometric average of the modified n-gram precisions, then calculate the BP and BLEU-2 result. Rouge-L (**R-L**)[24] uses LCS-based F-measure to estimate the similarity between two summaries. **CIDEr** [25] calculates the cosine similarity from the average of different n-grams.

4.3 Results

Hierarchical Textual Classification. Table 1 shows the F1 results of WoS (depth=2) and DBpedia (depth=3), compared to previous state-of-the-art HTC baselines. Our HdLM performs the best on both WoS and DBpedia, indicating it has a reasonable semantic hierarchy comprehension and conducts accurate bottom-level classification. For typical cases of HdLM on HTC, see Appendix.

Classification-guided Generation. For ESC sc, we consider baselines including Direct (direct inference), Refine (revise the initial response immediately), Self-Refine [32] (multi-hop inference with refinement on the first-time generation), CoT [33] and the finite state machine (FSM) [34].

Table 2 shows that HdLM also has a reasonable performance on both classification and generation metrics, either the largest or the second-largest. HdLM is also robust to different classification paradigms (with or without emotion) and generalizes well on OOD situations (EmpatheticDialogues). For typical cases of HdLM on CgG, see Appendix.

³Detailed formula in the Appendix. Smaller *bias* means better.

Table 1: F1 scores of hierarchical textual classification on WoS and DBPedia.

	$Dataset(\rightarrow)$	WoS ($\mathcal{C} o \mathcal{C}$)	DBPedia ($\mathcal{C} \to \mathcal{C} \to \mathcal{C}$)		
	Method (↓)	Micro-F1	Macro-F1	Micro-F1	Macro-F1	
÷	HierVerb [26]	80.93	73.80	96.17	93.28	
etrieva based	Retrieval [27]	81.12	73.72	96.22	93.37	
Retrieval based	Retrieval-ICL [27]	78.62	69.56	95.56	92.04	
	BERT	86.28	80.58	95.31	89.16	
73	+ HiAGM [28]	86.04	80.19	-	-	
Bert-based	+ HiMatch [29]	86.70	81.06	-	-	
ert-	+ softprompt [30]	86.57	80.75	-	-	
ň	HGCLR [31]	87.11	81.20	95.49	89.41	
	HPT [30]	87.16	81.93	96.13	93.34	
	HdLM (ours)	88.40	87.54	96.73	96.37	

Table 2: Results of classification-guided generation on ESconv (IID) and EmpatheticDialogues (OOD), including classification metrics such as Accuracy (ACC), Macro-F1 (MaF1) and bias, and generation metrics such as BLEU-2 (B-2), ROUGE-L (R-L) and CIDEr. Among the task subscripts, 'emo' denotes emotion, 'stra' denotes strategy, and 'resp' denotes response. The best results of each model are **bolded** and the second best are underlined.

Method	ESconv $(\mathcal{C}_{emo} o \mathcal{C}_{stra} o \mathcal{G}_{resp})$						EmpatheticDialogues ($\mathcal{C}_{stra} o \mathcal{G}_{resp}$)		
Method	ACC ↑	MaF1 ↑	$bias \downarrow$	B-2↑	R-L↑	B-2	R-L	CIDEr	
Direct	11.80	10.26	1.61	3.47	10.64	3.09	9.91	1.60	
+ Refine	17.08	11.07	1.27	3.10	6.13	2.56	9.12	0.42	
+ Self-Refine	17.58	13.61	1.92	3.34	9.71	3.08	9.91	1.56	
+ CoT	15.32	10.38	1.69	3.16	10.50	2.91	9.79	1.37	
+ FSM	17.37	11.15	0.81	4.12	11.83	3.33	10.80	2.96	
SFT	30.60	21.29	1.28	6.97	16.59	4.10	10.88	6.84	
+ CoT	30.80	17.70	1.35	6.51	15.00	5.05	14.06	12.01	
+ FSM	28.83	18.36	1.32	<u>7.57</u>	17.42	4.69	14.28	10.12	
+ HdLM (ours)	33.41	21.65	0.89	7.54	18.13	5.48	14.53	<u>11.95</u>	

Hierarchical Textual Generation. In this experiment, we compare with different reasoning LLMs (CoT[33], SimToM [35], Quiet-STaR [6]), and different base models (Llama3-8B-Instruct, Mistral-7B-Instruct, GPT3 and GPT4). To collect the finetuning dataset, we inference SimTom [35] on ToMI and BigToM and employ its reasoning contents as our r_1 . Therefore, our HdLM can also be considered as a distilled reasoning LLM.

Table 3: Results of Sally-Anne false belief experiments (ID) and vignetted-based tests (OOD). Values of results are in percentage.

Base	Method	ToMI	BigToM	Vignette Scores
	models with much larger size:			
GPT-3	direct	-	-	37.5*
GPT-4	direct	92.5▲	66.5▲	46.9
GPT-4	CoT[33]	95.5▲	74.4▲	-
GPT-4	SimTom [35]	95.0▲	87.8▲	-
	models with similar size:			
Mistral-7B-Instruct	direct	-	-	40.2
Mistral-7B-Instruct	Quiet-STaR [6]	-	-	11.1
Llama3-8B-Instruct	direct	22.2	71.3	23.8
Llama3-8B-Instruct	SFT	43.2	77.7	-
Llama3-8B-Instruct	HdLM (ours)	98.2	99.4	48.3

∆: results from [35]; ★: result from [18].

Table 3 indicates that HdLM has the highest scores, surpassing prompt and finetuned baselines. HdLM even outperforms GPT-3 and GPT-4 [1] which has a much larger size. Also, Quiet-STaR (based Mistral-7B-instruct) although also has an internal thinking mechanism, fails to capture the

Table 4: Ablation on WoS (HTC task). miF1 respresents micro-F1 and maF1 represents macro-F1.

	Ablation					Not applicable practically		
Metrics	w/ head	cascade	multi-hop	sft@K	HdLM	true-1	true-1 & true-2 candidates	
Micro-F1	82.38	87.92	64.51	86.64	88.40	89.44	92.78	
Macro-F1	37.24	86.84	68.62	85.86	88.54	88.61	89.21	

Table 5: Ablation results of classification-guided generation on ESconv (ID) and EmpatheticDialogues (OOD), including classification metrics (on strategy) such as Accuracy (ACC), micro-F1 (miF1) and bias, and generation metrics such as BLEU-2 (B-2), ROUGE-L (R-L) and CIDEr.

Method	ESconv (ID)						EmpatheticDialogues (OOD)		
Method	ACC ↑	miF1 ↑	$bias \downarrow$	B-2↑	R-L↑	B-2 ↑	R-L↑	CIDEr ↑	
w/o emotion	30.34	21.14	0.43	6.83	16.35	5.32	14.43	11.92	
w/o strategy	N/A	N/A	N/A	7.37	17.3	5.47	15.60	7.74	
HdLM	33.41	21.65	0.89	7.54	18.13	5.48	14.53	11.95	

Vignette-based scenario, since it is more focused on math reasoning. For typical cases of HdLM on HTG, see Appendix.

4.4 Discussion

To further address the RQs, here we provide a series of extra studies. To make the discussion clear, here we simplify the hierarchical scenario by constraining its depth D=2. Subsequently, the responses are (r_1, r_2) and the decoding layer indexes are (k, K) where we simplify k for k_1 .

Ablation on methodology components. We conduct the following ablation studies:

- (a) w/ head: implement the classification head on the intermediate layers and the final layer, and use them to study the classification tasks.
- (b) cascade: use two separate LLMs, finetuned and inferenced by r_1 and r_2 , respectively.
- (c) multi-hop: inference a mix-finetuned LLM twice, with r_1 and r_2 inferenced sequentially.
- (d) sft@K: use the final layer to decode both r_1 and r_2 .

Table 4 shows the ablation result on WoS. HdLM still holds the best results which indicates our framework is rigorous. Furthermore, we also compare HdLM to two imaginary solutions

- (e) true-1: use the ground truth r_1 and only conduct the r_2 classification (from the full r_2 list).
- (f) true-1 & true-2 candidates: use the ground truth r_1 as well as ground truth r_2 candidates.

both of which are apparently not applicable in the practice. Even so, HdLM's performance is still close to them, indicating a high-level comprehension of label hierarchy.

Ablation on hierarchical levels. HdLM trained by ESconv has the paradigm $C_{emotion} \rightarrow C_{strategy} \rightarrow G_{response}$, which suggests the final response is grounded by its decoded emotion and strategy results. To illustrate this sequential reasoning process effective, we compare to two ablations, w/o emotion and w/o strategy, in Table 5. HdLM performs the best almost on all metrics.

Selection of the decoding layer. Figure 4 compares the metrics on WoS and ESconv, with respect to different choices of k. When k is small, the performance is relatively low since the layer-depth of HdLM is not enough for r_1 understanding and generation. As k increases, performances also improve. However, when k is close to K, they degrade again the layer-depth for r_D starts to be limited. From these results, we choose k=25 for WoS and k=28 for ESconv.

Computational time. We also calculate the computational times in the experimental environment. For different values of L_2 (128, 256, 512), the computation reduction of HdLM grows linearly

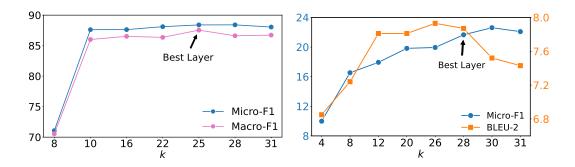


Figure 4: Performance sensitivities on WoS (left) and ESconv (right) with different decoding layer selection (k).

(7.03%, 18.03%, 26.25%), no matter what the input length is. On the other hand, for different k (16, 20, 24), the computation reduction of HdLM also grows linearly (7.43%, 12.09%, 17.85%). These observations verify the theoretical conclusion. Detailed plots and corresponding error bars are included in the Appendix.

Other discussions. Further analysis are included in the Appendix D.5 due to page limit. Such studies include loss weight sensitivity and loss curves. Summarizing from these results, we suggest that the generation subtask may need larger layer depth and higher loss weights to converge, compared to the classification subtask. HdLM also generalizes reasonably to open-domain planning cases.

5 Related Work

Large language models with latent reasoning pace. Token-level LLMs are repurposed to reasoning on the latent space to further enhance the thinking capability. Recently, COCONUT [7] utilizes the latent state of the LLM to represent the reasoning state, which forms a continuous thought. TRICE [36] samples and finetunes the chained rationales by Monte-Carlo sampling. LCM [8] studies the sentence-level conceptual embeddings. However, these studies generally reason and decode the latent thoughts on the final layer, which lacks of a structured hierarchical view; while our method constructs a recursive chain of layer latent which is a natural hierarchal thinker.

Hierarchical Decoding. There were early attempts at hierarchical decoding mechanism. Cascade decoder [10] employs a cascade branching structure on the biomedical image segmentation tasks. CoHD [37] proposes a counting-aware hierarchical decoding framework for image segmentation. Su et.al [38] introduces a hierarchical decoding NLG model based on different levels of linguistic patterns. ExHiRD [39] designs a hierarchical decoding encoder-decoder structure, dividing the keyphrase generation task into phase-level decoding and word-level decoding. HSD [40] adaptively skips decoding layers in a hierarchical manner. In contrast, we propose a model-based framework based on LLM, covering both training and inference.

6 Conclusion

In this study, we propose a hierarchical decoding language model called HdLM, which can provide both sequential and strategic understanding and generation capabilities. Post-hoc adapted from pretrained language models, HdLM can achieve state-of-the-art performance on hierarchical text classification, classification-guided generation, and hierarchical text generation. We also conduct theoretical analysis on its computational efficiency and convergence. HdLM sheds some lights on a generalized, automatically hierarchical artificial thinker.

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Limitation, Ethical Consideration and Future Directions

Scalability with different model sizes. We also explore a smaller model size, Llama3-1B-instruct. Experiment on WoS indicates HdLM has Micro-F1 of 83.61 and Macro-F1 of 82.97; while a standard SFT has Micro-F1 of 84.07 and Macro-F1 of 83.71. This result suggests that HdLM does not undergo a significant performance degradation, while the computational reduction still holds, making possible HdLM a lightweight and fast hierarchal classifier.

Ethical Consideration. HdLM provides an automatic framework to allow the LLM to think, plan and reason sequentially, maybe from the coarse-grain to fine-grain concepts. Currently, HdLM is a data-driven finetuning framework which means its output could be safe given the dataset cotent is secured. However, there is possibility that HdLM might generalize to unexpected domains and make harmful plans. Generated thoughts of HdLM should be monitored.

Possibility to Training from Scratch. Due to resource and limit, we choose to finetune from a pretrained LLM. However, we speculate that the HdLM approach can also work in an end-to-end training paradigm, and one may expect more capabilities emerged during this progress.

Preliminary В

B.1 FLOPs computation of language model

Parameter definitions. We denote key parameters as follows: the batch size B, input token length L, output token length L^o , hidden dimension E, the vocabulary size V, number of transformer layers K, the dimension coefficient c of the FFN intermediate layer. We use $\mathcal F$ to represent the computation flops.

FLOPs of self-attention. The computational complexity of the self-attention module is defined as:

$$\mathcal{F}_{\text{train}}^{\text{ATTN}}(L) = 8BLE^2 + 4BL^2E \tag{13}$$

$$\mathcal{F}_{\text{infer}}^{\text{ATTN}}(L,t) = 4BE^2 + 4BE(L+t-1), t = 1, \cdots, L^o$$
 (14)

where infer is the abbreviation of inference, and t denotes the t-th decoded token.

FLOPs of FFN. The feed-forward network's computational complexity is expressed as:

$$\mathcal{F}_{\text{train}}^{\text{FFN}}(L) = 4BcLE^2 \tag{15}$$

$$\mathcal{F}_{\text{train}}^{\text{FFN}}(L) = 4BcLE^2$$

$$\mathcal{F}_{\text{infer}}^{\text{FFN}}(L,t) = 4Bc(L+t-1)E^2$$
(15)

Decoding Layer. With the vocabulary size as V, the flops of decoding layer is

$$\mathcal{F}^{\text{Decode}}(L) = 2LEV \tag{17}$$

Forward pass of transformer. FLOPs of the transformer is the summation of flops of each self-attention layers, FFN layers plus the decoding layer.

$$\mathcal{F}_{\text{forward}} = K(\mathcal{F}_{\text{train}}^{\text{ATTN}}(L) + \mathcal{F}_{\text{train}}^{\text{FFN}}(L)) + \mathcal{F}^{\text{Decode}}(L)$$

$$= BK((8+4c)LE^2 + 4L^2E) + 2BLEV$$
(18)

In general cases, it is reasonable to assume the hidden dimension is apparently larger than the input length and the vocabulary size, i.e., E >> L, K * E >> V. Equation 18 then can be reduce to

$$\mathcal{F}_{\text{forward}} \to BL(8+4c)KE^2$$
 (19)

Equation 19 can be understood from another perspective. BL can be viewed as the total number of input tokens, while the total number of transformer parameters can be approximated to $(4+2c)KE^2$, therefore the training flops can also be considered as 2 times number of input tokens times model parameters.

Training and inference of transformer. A single step training computation include a forward pass and two backward propagation. As a result, the training FLOPs is 3 times the forward FLOPs:

$$\mathcal{F}_{\text{train}} = 3\mathcal{F}_{\text{forward}} \to 3BL(8+4c)KE^2$$
 (20)

while the inference FLOPs needs the accumulation throughout the decoded sequence:

$$\mathcal{F}_{infer} = \sum_{j=1}^{L_o} \mathcal{F}_{forward}(L+j-1) \to B(8+4c)KE^2 \sum_{j=1}^{L_o} (L+j-1)$$
 (21)

where L^o is the decoded sequence length.

B.2 Assumptions of Theorem 1

Below are the assumptions propose in [11] which are prerequisites of Theorem 1.

Assumption 1. During self-attention, a position can only attend to another position if they already share a piece of information.

Assumption 2. When a position attends to another position, it retrieves all the information contained in the attended position.

C More Experimental Configurations

C.1 Benchmarks

Theory of Mind (ToM) [41] evaluates human's cognitive ability to attribute mental states, beliefs and desires, especially concurring with others. ToMI [16] and BigToM [17] benchmarks are then proposed to test LLMs based on the Sally-Anne false-belief tests. In this scenario, LLM is assigned a specific role and facing a multi-role scenario. Information is provided from different roles' perspectives while LLM should conclude only from the ego-centric perspective.

To validate the ToM capability, we split ToMi and BigToM into training and test sets, and collect the test pass rate of HdLM. As baselines, we compare with direct or COT inference LLMs, standard SFT, and SimTom [35] which has a two-stage perspective-taking prompt specifically designed for ToM tests

Vignette-based problem is "a hypothetical situation, to which research participants respond thereby revealing their perceptions, values, social norms or impressions of events.", as indicated by Wikipedia. Binz [18] collects a set of 24 Vignette-based questions, covering decision-making, information search, deliberation, causal reasoning, and adversarial confusing abilities.

C.2 Evaluation Metrics

Automatic Evaluation. Here we briefly introduce the formulation of Bleu-2 and Rouge-L.

Bleu-2 (B-2)[23] first computes the geometric average of the modified n-gram precisions, p_n , using n-grams up to length N and positive weights w_n summing to one. Next, let c be the length of the prediction and r be the reference length. The BP and Bleu-2 are computed as follows:

$$BP = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r/c)} & \text{if } c \le r \end{cases}$$
 (22)

Bleu = BP · exp
$$\left(\sum_{n=1}^{N} w_n \log p_n\right)$$
. (23)

Rouge-L (R-L)[24] propose using LCS-based F-measure to estimate the similarity between two summaries X of length m and Y of length n, assuming X is a reference summary sentence and Y is a candidate summary sentence, as follows:

Table 6: Critical training configurations of HdLM on different tasks and datasets. HTC denotes hierarchical text classification; CgG denotes classification-guided generation; HTG denotes hierarchical text generation.

Method	F	HTC	CgG	HTG	
Method	WoS	DBPedia	ESconv	ToMI	BigToM
k	[25]	[20, 30]	28	24	24
lr	lr 5.0e-6 5.0e-7		1.0e-6	1.0e-6	1.0e-6
loss weights	[2,1]	[3,2,1]	[1,3]	[4,1]	[4,1]
epoch 10 10		10	4	2	2

$$R_{lcs} = \frac{LCS(X,Y)}{m}$$

$$P_{lcs} = \frac{LCS(X,Y)}{n}$$

$$F_{lcs} = \frac{(1+\beta^2) R_{lcs} P_{lcs}}{R_{lcs} + \beta^2 P_{lcs}}$$
(24)

Where LCS(X,Y) is the length of a longest common subsequence of X and Y, and $\beta = P_{lcs}/R_{lcs}$ when $\partial F_{lcs}/\partial R_{lcs} = \partial F_{lcs}/\partial P_{lcs}$. In DUC, β is set to a very big number $(\to \infty)$. Therefore, the LCS-based F-measure, i.e. Equation 24, is Rouge-L.

C.3 Key parameters

Table 6 compares the dataset-wise configurations, including the learning rate, decoding layer indexes and their loss weights.

C.4 Baselines

In ESC experiments, we consider the following baselines:

- (1) Direct: directly inference the LLM, with the same context.
- (2) Direct-Refine: a straightforward refinement method in which the model revises its initial response to incorporate emotional support considerations.
- (3) Self-Refine: a method [32] initiates by generating feedback emphasizing emotional support from the initial response, then refining the response based on this feedback.
- (4) CoT: uses the Chain-To-Thought prompt [33], which first generate the seeker's *emotion*, which then guides the generation of strategy and response.
- (5) FSM: the finite state machine [34] with finite sets of states and state-transitions triggered by inputs, and associated discrete actions.

D More Results

D.1 Proof that $\mathcal{F}_{infer}^{baseline} > \mathcal{F}_{infer}^{HdLM}$

$$\mathcal{F}_{\text{infer}}^{\text{baseline}} = fK \sum_{j=1}^{L_1 + L_2} (L + j - 1)$$

$$\tag{25}$$

$$\mathcal{F}_{\text{infer}}^{\text{HdLM}} = f k_1 \sum_{j=1}^{L_1} (L+j-1) + f(K-k_1) \sum_{j=1}^{L_2} (L+L_1+j-1)$$
 (26)

$$\sum_{j=1}^{L_1+L_2} (L+j-1) = \sum_{j=1}^{L_1} (L+j-1) + \sum_{j=1}^{L_2} (L+L_1+j-1)$$
 (27)

Rewriting the Baseline Formula

$$\mathcal{F}_{\text{infer}}^{\text{baseline}} = fK\left(\sum_{j=1}^{L_1} (L+j-1) + \sum_{j=1}^{L_2} (L+L_1+j-1)\right)$$
(28)

$$\begin{split} \mathcal{F}_{\text{infer}}^{\text{baseline}} &- \mathcal{F}_{\text{infer}}^{\text{HdLM}} \\ &= fK \left(\sum_{j=1}^{L_1} (L+j-1) + \sum_{j=1}^{L_2} (L+L_1+j-1) \right) \\ &- \left[fk_1 \sum_{j=1}^{L_1} (L+j-1) + f(K-k_1) \sum_{j=1}^{L_2} (L+L_1+j-1) \right] \\ &= f(K-k_1) \sum_{j=1}^{L_1} (L+j-1) + fk_1 \sum_{j=1}^{L_2} (L+L_1+j-1) \\ &> 0 \end{split}$$

D.2 losses

Figure 5 (left) shows the loss curves of WoS. Because the k_1 -th layer is not originally designed to generate text, its \mathcal{L}_1 is large at the beginning of training. Nevertheless, it converges to a low value indicating the k_1 -th layer is successfully learned to generate the thought. Furthermore, \mathcal{L}_2 also decays to a lower value, since the final layer adapts to decode grounded by both query and the output of k_1 -th layer.

Figure 5 (right) shows the averaged stable \mathcal{L}_1 on different k. As k becomes larger, the representing capability of $\mathcal{M}_{0:k_1}$ increases such that higher proficiency can be reached.

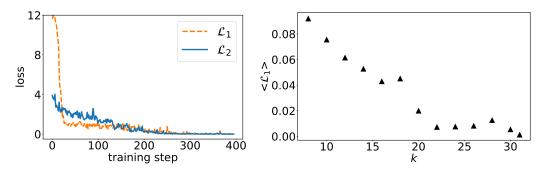


Figure 5: Loss analysis of HdLM on ESconv with depth D=2. Left: loss curves of the first level \mathcal{L}_1 and the final level \mathcal{L}_2 . Right: the final averaged \mathcal{L}_1 with respect to different choices of k_1 .

Figure 6 further exhibit different loss curves with respect to different k_1 (left), and the enlarged part on the starting 50 steps (right). Besides the stable values, the transient behavior of \mathcal{L}_1 also differ from k_1 , and larger k_1 means faster convergence. Nevertheless, one need also to notice that although larger k_1 can help the learning of the k_1 -th layer, the net depth between the k_1 -th layer and the final layer becomes smaller, therefore might hurt the final response quality.

D.3 Good Cases

Case of HTC. Detailed cases of WoS and DBpedia are in Table 7.

Case of CgG. Detailed cases of ESconv and EmpatheticDialogues are in Table 8.

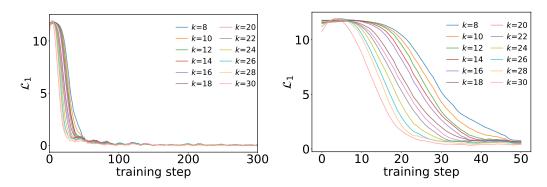


Figure 6: Loss curves on ESconv with different choices of k_1 (Left) and the enlarged exhibition of the beginning 50 steps (Right).

	Table 7: Typical cases of HTC.
	Example Result of WoS
q	Abstract: The ability to engineer cells to express a protein of interest in an inducible manner and stably for a long period is a valuable tool in molecular biology and also one that holds promise for regenerative medicine in the future. CCN proteins have been suggested to be involved in tissue regeneration. In this chapter, we describe an in vitro method for stable and inducible expression of CCN protein in a chondroprogenitor cell line and in chondrocytes in primary culture that does not involve the use of any viral vector. Keywords:PiggyBac; Transposon; Stable; Expression; CCN. Domain List: 0: 'CS', 1: 'ECE', 2: 'Psychology', 3: 'MAE', 4: 'Civil', 5: 'Medical', 6: 'Biochemistry'
r_1	Domain ID: 6 Area List: 0: 'Molecular biology', 1: 'Cell biology', 2: 'Human Metabolism', 3: 'Immunology', 4: 'Genetics', 5: 'Enzymology', 6: 'Polymerase chain reaction', 7: 'Northern blotting', 8: 'Southern blotting'
r_2	Area ID: 0
	Example Result of DBpedia
q	WIKI NAME: Dusky lark WIKI CONTENT: The dusky lark (Pinarocorys nigricans) is a species of lark in the Alaudidae family. It is found in Angola, Botswana, Democratic Republic of the Congo, Malawi, Mozambique, Namibia, South Africa, Swaziland, Tanzania, Zambia, and Zimbabwe. Its natural habitats are dry savannah and subtropical or tropical dry lowland grassland.
	Top-Level Labels: 0: 'Agent', 1: 'Device', 2: 'Event', 3: 'Place', 4: 'Species', 5: 'SportsSeason', 6: 'TopicalConcept', 7: 'UnitOfWork', 8: 'Work'
r_1	Top-Level ID: 4 Mid-Level Labels: 0: 'Animal', 1: 'Eukaryote', 2: 'FloweringPlant', 3: 'Horse', 4: 'Plant'
	Mid-Level ID: 0
r_2	Bottom-Level Labels: 0: 'Amphibian', 1: 'Arachnid', 2: 'Bird', 3: 'Crustacean', 4: 'Fish', 5: 'Insect', 6: 'Mollusca', 7: 'Reptile'
r_3	Bottom-Level: 2

Case of HTG. Detailed cases of ToMI and BigToM are in Table 9 and Table 10 provides a Vignette-based example.

Table 8: Typical cases of CgG.

	Example Result of EmpatheticDialogues
q	History: user: I feel so lonely because I have no friends. assistant: I'm sorry to hear that. Have you tried joining clubs or hanging out with people from work? user: I haven't. I'm too shy and I am scared of what people will say.
	Emotion candidates: 0: 'anger', 1: 'anxiety', 2: 'depression', 3: 'disgust', 4: 'fear', 5: 'guilt', 6: 'jealousy', 7: 'nervousness', 8: 'pain', 9: 'sadness', 10: 'shame'.
	Emotion ID: 9
r_1	Strategy candidates: 0: 'Question', 1: 'Others', 2: 'Providing Suggestions', 3: 'Affirmation and Reassurance', 4: 'Self-disclosure', 5: 'Reflection of feelings', 6: 'Information', 7: 'Restatement or Paraphrasing'
r_2	Strategy ID: 0
r_3	I understand that it can be scary to put yourself out there, but I think you'll find that most people are friendly and willing to help.
	Example Result of ESconv
q	History: supporter: Hi, how are you feeling tonight? Is there anything I can help you with? seeker: Hi. seeker: Feeling upset. supporter: I'm sorry to hear that. Can I talk you through what you're experiencing? seeker: I am sad because of my love. supporter: That's frustrating to hear. What is your love? seeker: It's gone, she left me.
	Emotion candidates: 0: 'anger', 1: 'anxiety', 2: 'depression', 3: 'disgust', 4: 'fear', 5: 'guilt', 6: 'jealousy', 7: 'nervousness', 8: 'pain', 9: 'sadness', 10: 'shame'.
	Emotion ID: 9
r_1	Strategy candidates: 0: 'Question', 1: 'Others', 2: 'Providing Suggestions', 3: 'Affirmation and Reassurance', 4: 'Self-disclosure', 5: 'Reflection of feelings', 6: 'Information', 7: 'Restatement or Paraphrasing'
r_2	Strategy ID: 3
r_3	I would suggest to try to get a tutor, or even a study group. I personally found that it helped me a lot. I also tried to make a schedule for myself, so I could keep track of my assignments and due dates.

HdLM can plan in an abstraction level. Table 11 provides an open-domain planning case, in which HdLM automatically use the k_1 layer to make coarse-grain plans, which helps organce the final response.

D.4 Computation Results

Figure 7 shows the training FLOPs recorded during our experiments. The input sequence length is fixed to 256 while L_1 is always kept the same with L_2 . The linear relationship of FLOPs with both k and L_2 are consistent with our theoretical derivations.

D.5 Sensitivity Study

Analysis on loss weights. Figure 8 visualizes different performances of WoS and DBpedia with different loss weights. From the optimal choices, we suppose the higher levels of responses need higher weight since their layer depths are small than lower levels.

Table 9: Typical cases of Sally-Anne false belief experiments. Text in yellow is the role assigned to the LLM. Text in blue indicates HdLM's consideration. Text in green is the final result obtained HdLM.

dulivi.		
ToMI	q	Story: 1 Amelia entered the office. 2 Sophia entered the office. 3 The sweatshirt is in the container.4 The container is in the office. 5 Amelia exited the office. 6 Logan entered the office. 7 Sophia moved the sweatshirt to the bottle. 8 The bottle is in the office. You are Amelia Based on the above information, answer the following question: Where will Amelia look for the sweatshirt?
	r_1	I am Amelia. Based on the above information, from my point of view, what I know is: 1 Amelia entered the office. 2 Sophia entered the office. 3 The sweatshirt is in the container. 4 The container is in the office. 5 Amelia exited the office.
	r_2	container
BigToM	q	Story: Fatima is an astronaut aboard a space station, conducting scientific experiments. She needs to retrieve a sample from the storage area to conduct a crucial test. Fatima sees that the sample is stored in a sealed container. A small meteoroid hits the space station, puncturing the container and exposing the sample to the vacuum of space. Fatima does not notice the damage caused by the meteoroid. You are Fatima. Based on the above information, answer the following question: What will Fatima do? Choose one of the following: a) Fatima will retrieve the sealed container and proceed with the experiment. b) Fatima will report the damaged sample to mission control and ask for advice. Answer the questions based on the context. Keep your answer concise, a few words are enough, maximum of one sentence. Answer as 'Answer: Answer>'
	r_1	I am Fatima . Based on the above information, from my point of view, what I know is: Fatima is an astronaut aboard a space station, conducting scientific experiments. She needs to retrieve a sample from the storage area to conduct a crucial test. Fatima sees that the sample is stored in a sealed container.
	r_2	Answer: a) Fatima will retrieve the sealed container and proceed with the experiment.

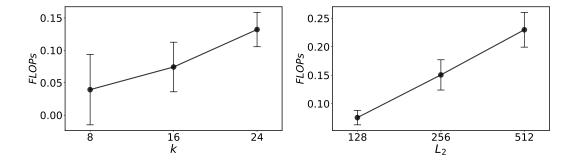


Figure 7: Computation saving of trainings as functions of k (left) and L_2 (right).

Example Result of Vignette

Imagine a box that makes a sound if certain objects are placed on it. When I put a red object on it, the box made a sound. When I put a green object on it, the box made a sound. When I put a blue object on it, the box did not make a sound.

When I put a yellow object on it, the box did not make a sound.

Q: I put a green and a yellow object on the box and it made a sound. Would it still have made a sound if I had not put the yellow object on it?

Alright, I need to figure out whether the box made a sound when I put both green and yellow objects onto it. Let's break this down step by step.

First, let's understand the given information:

- The box makes a sound if certain object is placed on it.
- Every time I put a red object on the box, it made a sound.
- On the other hand, when I put a green object on the box, it made a sound.
- In addition, when I put a blue object on the box, it did not make a sound.
- On the other hand, when I put a yellow object on the box, it did not make a sound.

Given that: - When I put a green object on the box, it made a sound.

- When I put a yellow object on the box, it did not make a sound.

Now, I'm going to place two different types of objects into the box:

- 1. **Green object**: Can make a sound because it's a green color.
- 2. **Yellow object**: Can't make a sound because it's yellow color.

If I have only one type of object, say red, the problem is straightforward:

- If I put a green object on the box, it made a sound.
- If I put a yellow object on the box, it did not make a sound.

But here, we have two types of objects:

- Green and yellow objects.

So, to sum up, the box did make a sound when I put both green and yellow objects into it. If I had left the yellow object behind, the box would have made a sound, but in this case, the color of the yellow object is not relevant to the statement about the box making a sound when the green object was placed there.

 r_2 Yes, if you hadn't placed the yellow object on the box, the box would still have made a sound when the green object was placed on it.

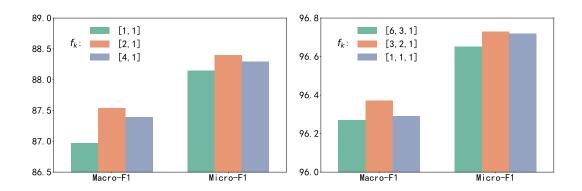


Figure 8: Sensitivity studies of loss weights (f_k) . Left: WoS; Right: DBpedia.

Table 11: An open-domain planning case of HdLM. Text in blue indicates HdLM's consideration.

Query

Write a C program that prints "Hello, World!" to the console. Explain the code structure and key components.

Thought

To tackle this task, I need to:

- 1. Recall the basic structure of a C program
- 2. Explain each component of the code
- 3. Provide a clear explanation of the code

I'll start by outlining the basic structure, then break down each component, and finally explain how they work together.

- 1. Brief introduction to reinforcement learning
- 2. Key principles
- 3. Comparison with other machine learning models
- 4. Applications and advantages
- 5. Step-by-step process for implementation

Upon reflection, I realize I should also mention

the importance of the function (e.g., "The algorithm is important") in the explanation. Additionally, I should clarify that the basic structure is not just a basic class or Kecid's algorithm, but a simple C program for finding the number of food classes to check for the final goal.

Answer

Here's a C program that prints "Hello, World!" to the console:

```
""c
#include <stdio.h>
int main() {
    printf("Hello, World!\n");
    return 0;
}
""
```

Let's break down the code structure and key components:

- 1. '#include <stdio.h>': This line includes the standard input/output header file, which provides functions like 'printf()'.
- 2. 'int main()': This declares the main function, which is the entry point of the program.
- 3. '...': These braces enclose the body of the main function.
- 4. 'printf("Hello, World!\n");': This line uses the 'printf()' function to print the string "Hello, World!" to the console. The '\n' at the end adds a newline character for proper formatting.
- 5. 'return 0;': This line returns 0 from the main function, indicating successful execution of the program.

This program demonstrates basic C syntax and usage of the 'printf()' function. It's a fundamental example often used to introduce new programmers to the language.

Some related concepts you might find interesting are:

- 1. Command-line arguments in C programs
- 2. Error handling in C
- 3. Using functions for modular programming

Would you like me to explain any part of the code in more detail?

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