RouterDC: Query-Based Router by Dual Contrastive Learning for Assembling Large Language Models

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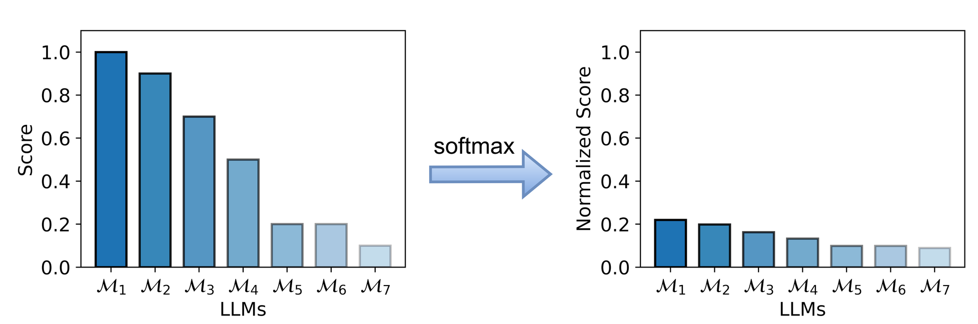
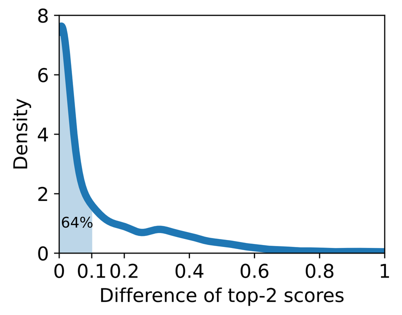
PAPER CODE

Background

- Large language models (LLMs) have demonstrated proficient capabilities across various tasks. They typically exhibit **varying strengths and weaknesses** across different tasks. Assembling multiple off-the-shelf LLMs can harness their complementary abilities, resulting in better performance than relying on a single LLM.
- Routing is a promising assembling method which **learns a router to select a suitable LLM for each query**. Compared with LLM ensembling, routing is much more efficient as it only needs to perform inference on the selected LLM.
- ZOOTER (NAACL, 2024) scores LLMs for each query, then minimizes Kullback-Leibler divergence between selection probability from the router and the softmax normalized score. However, when multiple LLMs perform well for a query, the normalized score tends to be uniform, which is not a strong supervision signal for learning the router.



(a): Score distributions of LLMs on an example query (w/ or w/o normalization).



(b): Distribution of the score difference between the top two LLMs.

Scoring

Consider a set of LLMs $\{\mathcal{M}_t : t = 1, \ldots, T\}$ and a training set $\mathcal{D}_{\text{train}} = \{(\mathbf{x}_i, y_i) : i = 1, \ldots, n\}$, where $\mathbf{x}_i$ is a query (i.e., question) and y_i is its answer (i.e., ground truth). We design a scoring method to assess the performance of LLMs on queries.

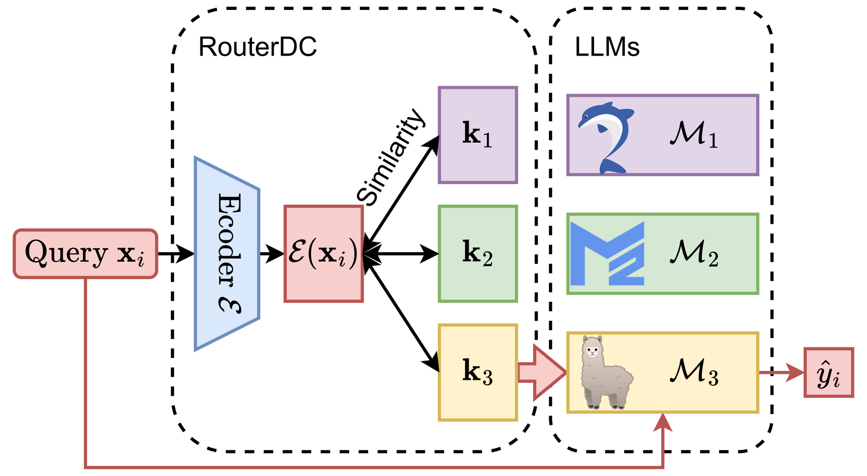
- For an *open-ended* generation query $\mathbf{x}_i$ (requiring a long answer, e.g., GSM8K), we feed it to LLM M times to generate outputs $\{\hat{y}_{i,m}^{(t)} : m = 1, \ldots, M\}$, then define the score of LLM $\mathcal{M}_t$ on the query x_t as:

$$s_i^{(t)} = \frac{1}{M} \sum_{m=1}^{M} \text{evaluate}(\hat{y}_{i,m}^{(t)}, y_i)$$

- For a *multiple-choice question* $\mathbf{x}_i$ with an option set $\mathcal{A}_i$ (e.g., MMLU), we define the score based on the probability of options, i.e.,

$$s_i^{(t)} = \begin{cases} \frac{\mathbb{P}_{\mathcal{M}_t}(\hat{y}_i^{(t)} | \mathbf{x}_i)}{\sum_{a \in \mathcal{A}_i} \mathbb{P}_{\mathcal{M}_t}(a | \mathbf{x}_i)} & \text{if} \quad \hat{y}_i^{(t)} = y_i \\ 0 & \text{otherwise} \end{cases}$$

RouterDC Framework



The proposed RouterDC consists of

- An encoder $\mathcal{E}(\mathbf{x}; \mathbf{w})$ parameterized by $\mathbf{w}$ which maps $\mathbf{x}$ into an embedding in $\mathbb{R}^p$.
- T learnable LLM embeddings $\{\mathbf{k}_t \in \mathbb{R}^p : t = 1, \ldots, T\}$ for the T LLMs.

For a query $\mathbf{x}_i$, RouterDC generates a selection probability distribution over T LLMs as

$$R(\mathbf{x}_i; \boldsymbol{\theta}) = \text{softmax}\left[\text{sim}(\mathcal{E}(\mathbf{x}_i; \mathbf{w}), \mathbf{k}_1), \ldots, \text{sim}(\mathcal{E}(\mathbf{x}_i; \mathbf{w}), \mathbf{k}_T)\right],$$

where $\boldsymbol{\theta} \equiv \{\mathbf{w}, \mathbf{k}_1, \mathbf{k}_2, \ldots, \mathbf{k}_T\}$ is the learnable parameters in RouterDC and $\text{sim}(\cdot, \cdot)$ is the cosine similarity.

Dual Contrastive Loss

Sample-LLM Contrastive Loss

- Based on the score, we construct positive LLMs index set $\mathcal{I}_i^+$ and negative LLMs index set $\mathcal{I}_i^-$ as:
  1. $\mathcal{I}_i^+$ consists of the indices of LLMs corresponding to the top-K_+ scores.
  2. $\mathcal{I}_i^-$ consists of the indices of LLMs corresponding to the bottom-K_- scores with $s_i^{(t)} < 0.5$.
- We expect the router to pull the query embedding $\mathcal{E}(\mathbf{x}_i; \mathbf{w})$ closer to the positive LLMs' embeddings $\{\mathbf{k}_{t_+} : t_+ \in \mathcal{I}_i^+\}$ while pushing apart from the negative LLMs' embeddings $\{\mathbf{k}_{t_-} : t_- \in \mathcal{I}_i^-\}$.

$$\mathcal{L}_{\text{sample-LLM}}(\mathbf{x}_i, y_i; \boldsymbol{\theta}) = \sum_{t_+ \in \mathcal{I}_i^+} -\log \frac{e^{\text{sim}(\mathcal{E}(\mathbf{x}_i;\mathbf{w}),\mathbf{k}_{t_+})}}{e^{\text{sim}(\mathcal{E}(\mathbf{x}_i;\mathbf{w}),\mathbf{k}_{t_+})} + \sum_{t_- \in \mathcal{I}_i^-} e^{\text{sim}(\mathcal{E}(\mathbf{x}_i;\mathbf{w}),\mathbf{k}_{t_-})}}$$

Sample-Sample Contrastive Loss

- Minimizing the sample-LLM contrastive loss alone is not stable. Some similar queries can have dissimilar embeddings and may be routed to different LLMs.
- Training samples are grouped into N groups $\{\mathcal{K}_1, \ldots, \mathcal{K}_N\}$ by applying k-means algorithm on extracted t-SNE low-dimensional vectors. For a query $\mathbf{x}_i \in \mathcal{K}_j$, we randomly select an in-group query $\mathbf{x}_i^+ \in \mathcal{K}_j$ and an out-group set $\mathcal{X}_i^- \subset \{\cup_{j' \neq j} \mathcal{K}_{j'}\}$ of H queries from the training mini-batch at each iteration.

$$\mathcal{L}_{\text{sample-sample}}(\mathbf{x}_i; \boldsymbol{\theta}) = -\log \frac{e^{\text{sim}(\mathcal{E}(\mathbf{x}_i;\mathbf{w}),\mathcal{E}(\mathbf{x}_i^+;\mathbf{w}))}}{e^{\text{sim}(\mathcal{E}(\mathbf{x}_i;\mathbf{w}),\mathcal{E}(\mathbf{x}_i^+;\mathbf{w}))} + \sum_{\mathbf{x}_i^- \in \mathcal{X}_i^-} e^{\text{sim}(\mathcal{E}(\mathbf{x}_i;\mathbf{w}),\mathcal{E}(\mathbf{x}_i^-;\mathbf{w}))}}.$$

Training

- We learn a router $R(\mathbf{x}; \boldsymbol{\theta})$ by minimizing the final objective consisting of sample-LLM and sample-sample contrastive losses, i.e.,

$$\mathcal{L}(\mathcal{D}_{\text{train}}; \boldsymbol{\theta}) = \sum_{(\mathbf{x}_i, y_i) \in \mathcal{D}_{\text{train}}} \mathcal{L}_{\text{sample-LLM}}(\mathbf{x}_i, y_i; \boldsymbol{\theta}) + \lambda\, \mathcal{L}_{\text{sample-sample}}(\mathbf{x}_i; \boldsymbol{\theta})$$

Experiments

Table 1: Testing accuracy ($\%$) on in-distribution tasks. "Time" denotes the total inference time in minutes.

		MMLU	GSM8K	CMMLU	ARC-C	HumanEval	Avg	Time (m)
Candidate LLMs	Mistral-7B	62.14	36.71	43.83	49.43	28.98	44.22	6.94
	MetaMath-Mistral-7B	59.86	69.63	43.83	48.30	29.80	50.28	7.23
	zephyr-7b-beta	59.81	33.00	42.82	<u>57.95</u>	22.04	43.13	6.73
	Chinese-Mistral-7B	57.42	41.03	<u>49.67</u>	43.47	21.43	42.60	7.11
	dolphin-2.6-mistral-7b	60.53	52.38	43.71	52.56	45.10	50.86	6.91
	Meta-Llama-3-8B	**64.59**	47.76	**51.77**	49.43	26.73	48.06	6.33
	dolphin-2.9-llama3-8b	59.46	<u>69.81</u>	44.72	49.43	<u>49.39</u>	54.56	5.33
	Voting	63.30	67.39	47.48	50.85	42.85	54.37	46.59
Routing	CosineClassifier	59.72	69.03	45.47	50.57	46.33	54.22	8.30
	ZOOTER	60.48	66.69	45.27	53.13	44.29	53.97	8.01
	LoraRetriever (clustering)	<u>63.33</u>	66.63	**51.77**	57.10	40.00	<u>55.77</u>	7.86
	RouterDC	61.07	**70.32**	**51.77**	**58.52**	**51.02**	**58.54**	7.97

- RouterDC achieves the **highest** average accuracy, surpassing the best individual LLM (i.e., dolphin-2.9-llama3-8b)
- RouterDC is **better** than ZOOTER and CosineClassifier, demonstrating that the proposed dual contrastive losses can train a more effective router. RouterDC **outperforms** LoraRetriever, validating the usefulness of the sample-LLM contrastive loss.
- RouterDC is about $6\times$ **faster** in inference than voting.

Table 2: Testing accuracy ($\%$) on out-of-distribution tasks. "Time" denotes the total inference time in minutes.

		PreAlgebra	MBPP	C-EVAL	Avg	Time (m)
Candidate LLMs	Mistral-7B	24.80	37.90	46.43	36.38	4.31
	MetaMath-Mistral-7B	<u>39.15</u>	37.74	45.17	40.69	4.13
	zephyr-7b-beta	20.78	31.14	44.87	32.26	4.30
	Chinese-Mistral-7B	18.48	29.64	48.44	32.19	4.40
	dolphin-2.6-mistral-7b	29.28	44.86	45.10	39.75	3.20
	Meta-Llama-3-8B	27.67	43.02	**52.01**	40.90	3.95
	dolphin-2.9-llama3-8b	**39.72**	**47.34**	44.80	<u>43.95</u>	3.15
	Voting	39.03	41.60	48.50	43.04	27.43
Routing	CosineClassifier	36.97	38.48	47.77	41.07	4.43
	ZOOTER	34.44	41.10	44.95	40.16	4.28
	LoraRetriever (clustering)	35.36	43.12	**52.01**	43.50	4.22
	RouterDC	38.81	<u>46.80</u>	<u>51.93</u>	**45.85**	4.24

Summary

- Problem: harness the complementary abilities of LLMs.
- Propose a novel routing method RouterDC and two contrastive losses to train the router.
- Experimental results show that RouterDC effectively assembles LLMs and outperforms individual top-performing LLMs as well as existing routing methods.