Towards Unified Task Embeddings Across Multiple Models: Bridging the Gap for Prompt-Based Large Language Models and Beyond

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Task Embedding

- Task Embedding is a meta-learning tool for capturing the task-specific information of a task.
- Existing task embedding methods rely on fine-tuned, task-specific language models. Such approach is limited to the single-model scenarios, and is not applicable for LLMs.
- In this paper, we introduce a new framework, capable of learning unified task embeddings from diverse models, including language models of different architectures, and LLMs with various prompts, within a single vector space.

Background

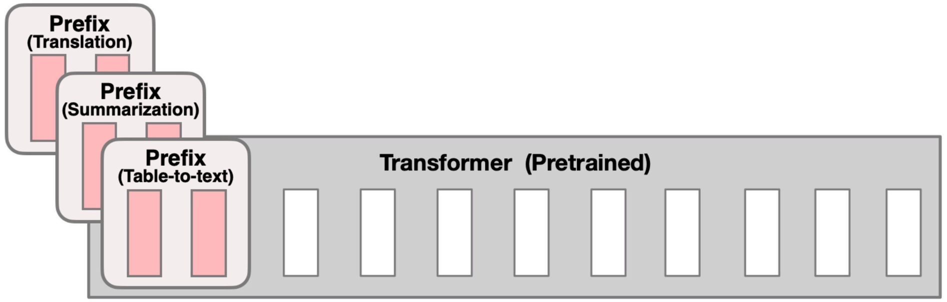
TaskEmb:

- computes the empirical Fisher on a fine-tuned model as task embedding

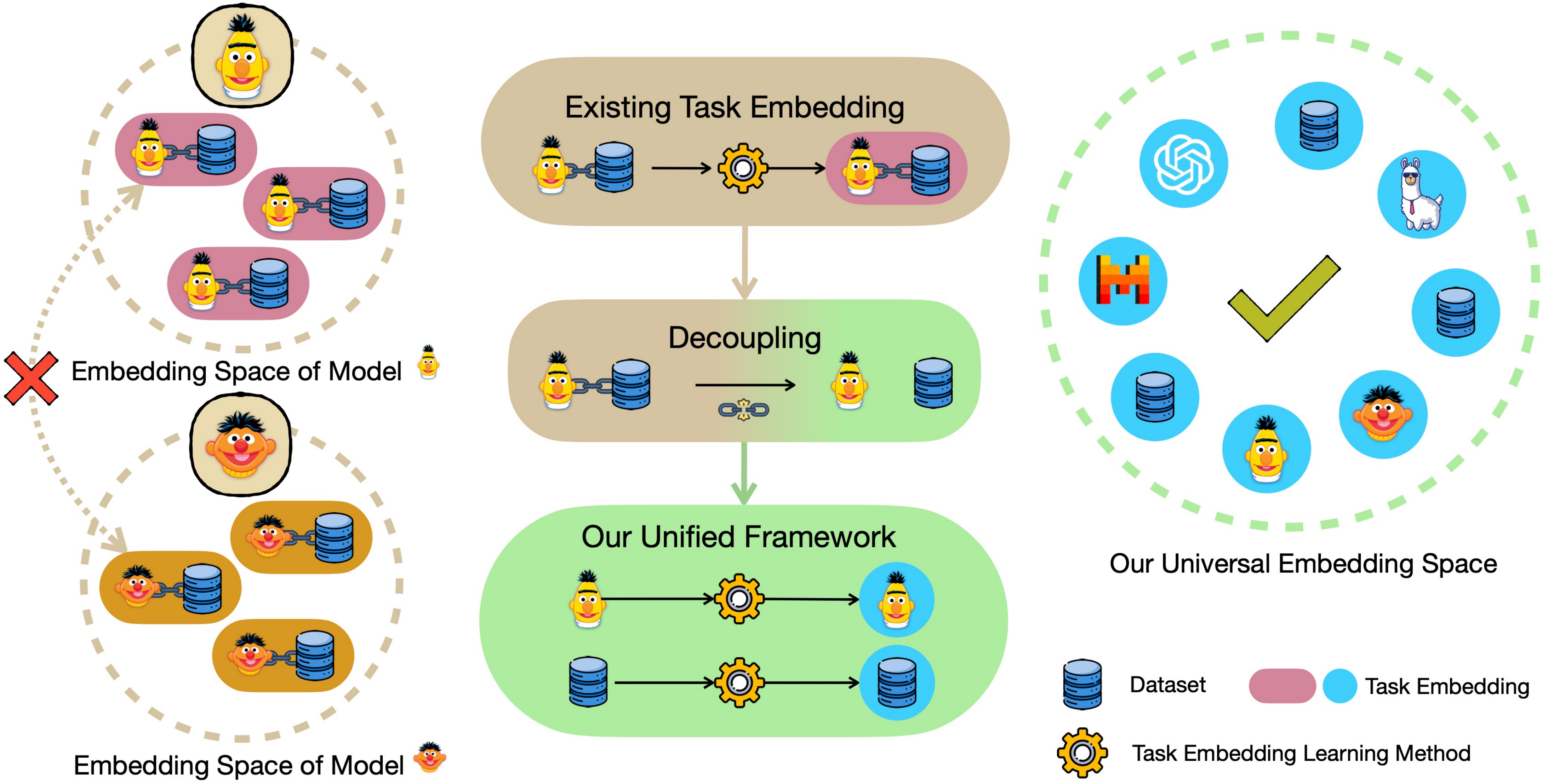
$$F_\theta = \frac{1}{n}\sum_{i=1}^{n}\left[\nabla_\theta \log P_\theta(y_i|x_i)\nabla_\theta \log P_\theta(y_i|x_i)^T\right]$$

TuPaTE:

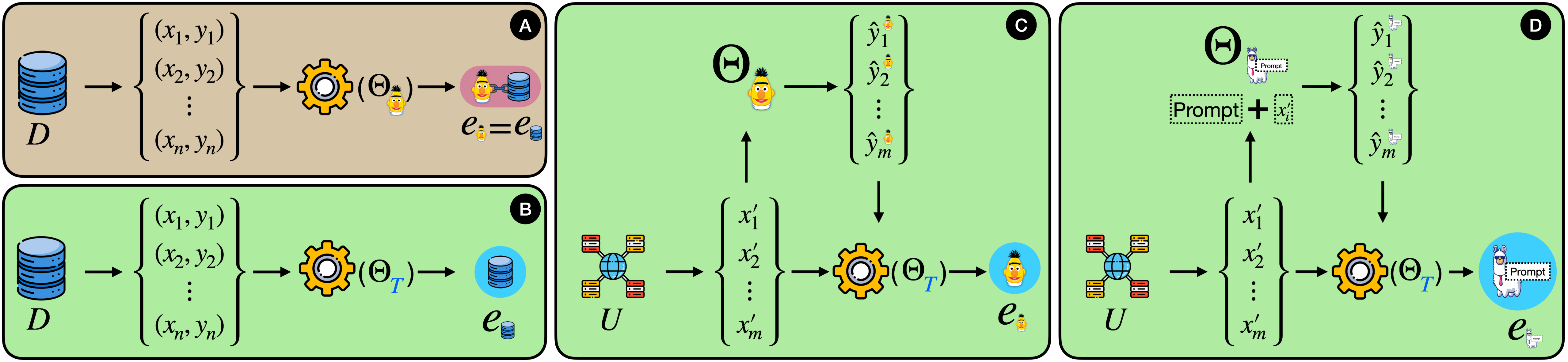
- utilizes Parameter-Efficient FineTuning (PEFT) methods on a language model and extract the tuned parameters as the task embedding.



Our Framework



Our Methods



D: Dataset; U: Unsupervised Dataset;

T: surrogate base model; e: Task Embedding

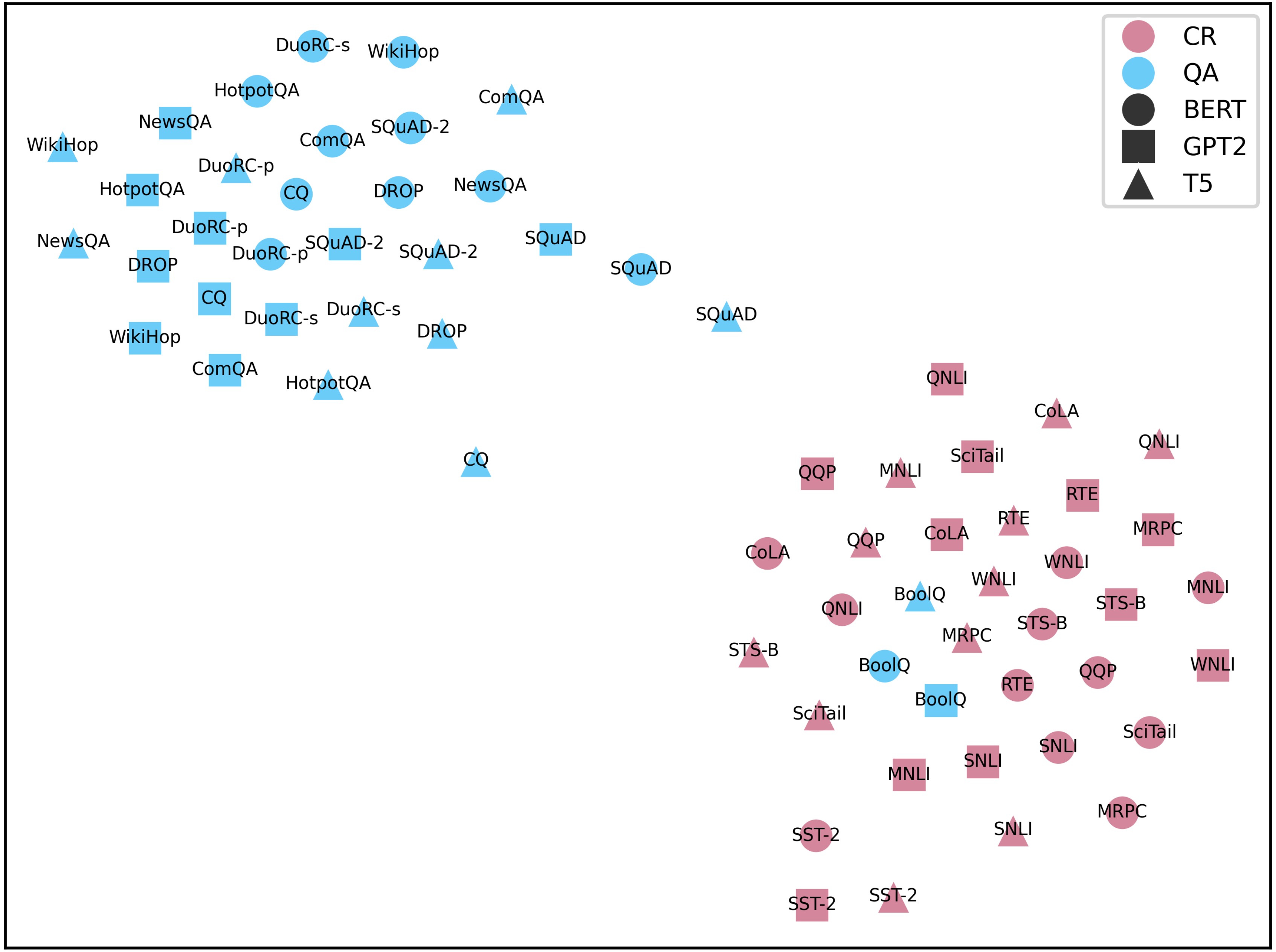
Visualization

Task embeddings from our framework extracted from different language model fine-tuned on different datasets.

CR: Classification or Regression task.

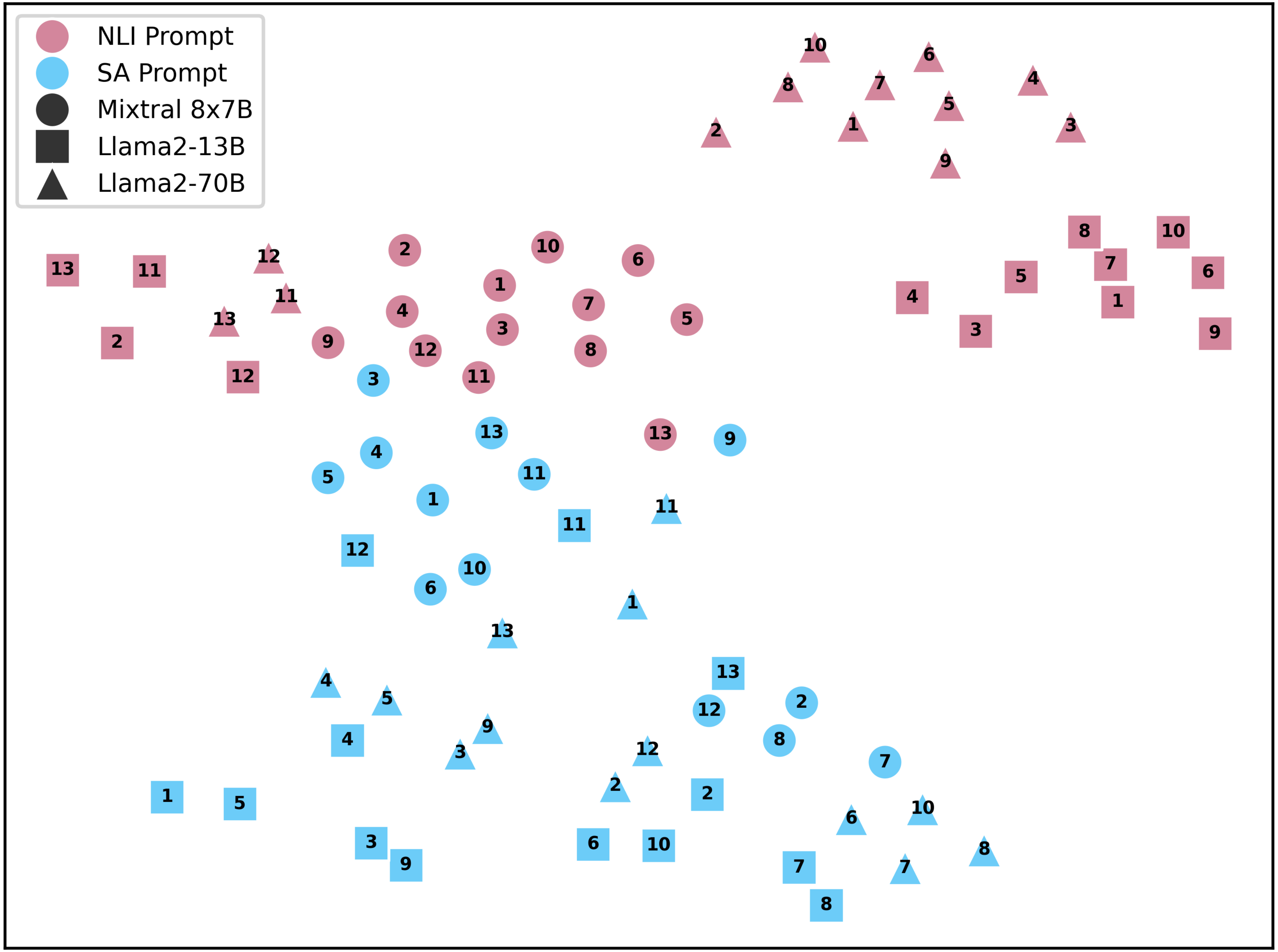
QA: Question Answering task.

(BoolQ is a boolean answer task, which is more similar to CR task.)



Visualization

Task embeddings from our framework extracted from different LLMs guided by different prompts.



NLI: Natural Language Inference.

SA: Sentiment Analysis.

1-10: Vanilla prompts.

11-13: CoT prompts.

(Check paper for detailed prompts)

Experiments

- Transferability experiments: selecting the best source dataset transferred to the target dataset based on the task embedding.
- Our framework retains a performance to be comparable to the existing model-specific methods

Method	CR				QA			
	in-class		*all-class*		*in-class*		*all-class*	
	$\rho\downarrow$	NDCG $\uparrow$	$\rho\downarrow$	NDCG $\uparrow$	$\rho\downarrow$	NDCG $\uparrow$	$\rho\downarrow$	NDCG $\uparrow$
DataSize	3.6	80.4	7.8	75.2	3.2	84.4	11.4	65.8
CurveGrad	5.5	68.6	-	-	8.3	64.8	-	-
TextEmb	5.2	76.4	9.8	74.7	4.1	81.1	5.8	82.0
TaskEmb	2.8	82.3	5.4	78.3	3.2	84.5	5.4	82.8
TuPaTE	**2.5**	83.7	**4.5**	81.0	**3.0**	**85.7**	4.8	83.3
FUTE + TaskEmb	4.4	79.4	7.0	77.9	4.5	83.5	5.3	84.3
FUTE + TuPaTE	3.3	**83.8**	6.2	**82.0**	3.3	85.6	**4.1**	**84.8**

Experiments

- Prompts selection experiments: selecting the best prompts based on the task embedding.
- Our framework also shows comparable performance to other prompts selection methods.

Category	Method	Llama 2 13B Performance	Llama 2 13B Rate	Llama 2 13B NDCG	Llama 2 70B Performance	Llama 2 70B Rate	Llama 2 70B NDCG	Mixtral 8x7B Performance	Mixtral 8x7B Rate	Mixtral 8x7B NDCG
SA	MI	88.0	94.4	59.0	85.3	90.9	72.9	87.2	85.1	65.1
	LocalE	84.3	90.2	47.5	88.3	88.7	57.5	**88.5**	**96.7**	78.6
	GlobalE	89.2	95.7	88.8	91.9	97.9	**82.7**	88.4	96.6	**86.7**
	ZPS-Log	54.3	58.2	38.5	78.0	83.0	54.0	57.0	62.1	33.9
	ZPS-Prob	54.3	58.2	38.5	78.0	83.0	50.8	57.0	62.1	33.9
	ZPS-Vote	54.3	58.2	38.5	78.0	83.0	50.8	57.0	52.1	33.9
	Self-Select	54.3	58.2	42.8	85.3	90.9	69.3	57.0	62.1	38.5
	SPELL	89.2	95.7	**89.6**	79.6	84.6	65.4	57.0	62.1	38.2
	FUTE + TaskEmb	**89.6**	**96.1**	89.4	**93.0**	**99.0**	74.5	86.9	94.9	71.1
	FUTE + TuPaTE	89.2	95.7	55.6	92.4	98.4	67.9	87.9	95.8	52.2
NLI	MI	**46.8**	**90.1**	61.7	48.6	94.8	74.6	37.2	73.6	36.7
	LocalE	37.5	74.4	56.4	43.9	84.6	66.6	39.1	78.6	43.5
	GlobalE	40.4	80.4	65.3	48.2	93.7	76.9	40.2	79.1	44.1
	ZPS-Log	34.8	70.2	48.1	34.9	66.8	49.5	39.0	76.5	41.7
	ZPS-Prob	32.6	65.6	39.7	38.0	73.2	51.2	39.5	78.9	39.3
	ZPS-Vote	32.6	65.6	39.7	33.7	64.3	48.4	39.5	78.9	39.3
	Self-Select	33.9	68.1	39.5	39.7	76.7	53.6	39.1	78.6	43.9
	SPELL	42.4	84.4	**78.1**	48.6	94.8	77.2	39.1	78.6	41.5
	FUTE + TaskEmb	35.8	72.0	47.4	41.1	78.8	60.8	**43.2**	**85.6**	**49.1**
	FUTE + TuPaTE	37.0	75.0	71.8	**50.6**	**98.4**	**81.8**	40.8	81.3	44.4

Thank you!