



Learning to Compress: Unlocking the Potential of Large Language Models for Text Representation

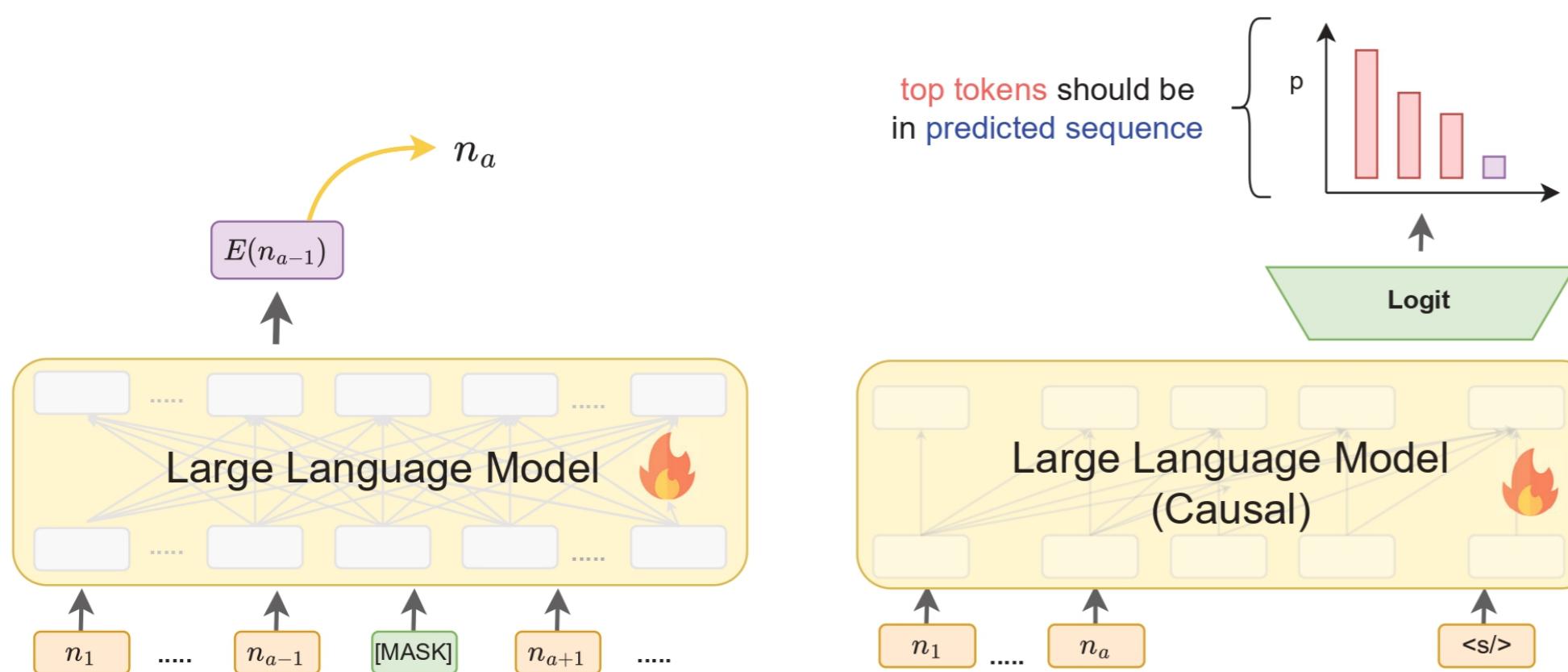
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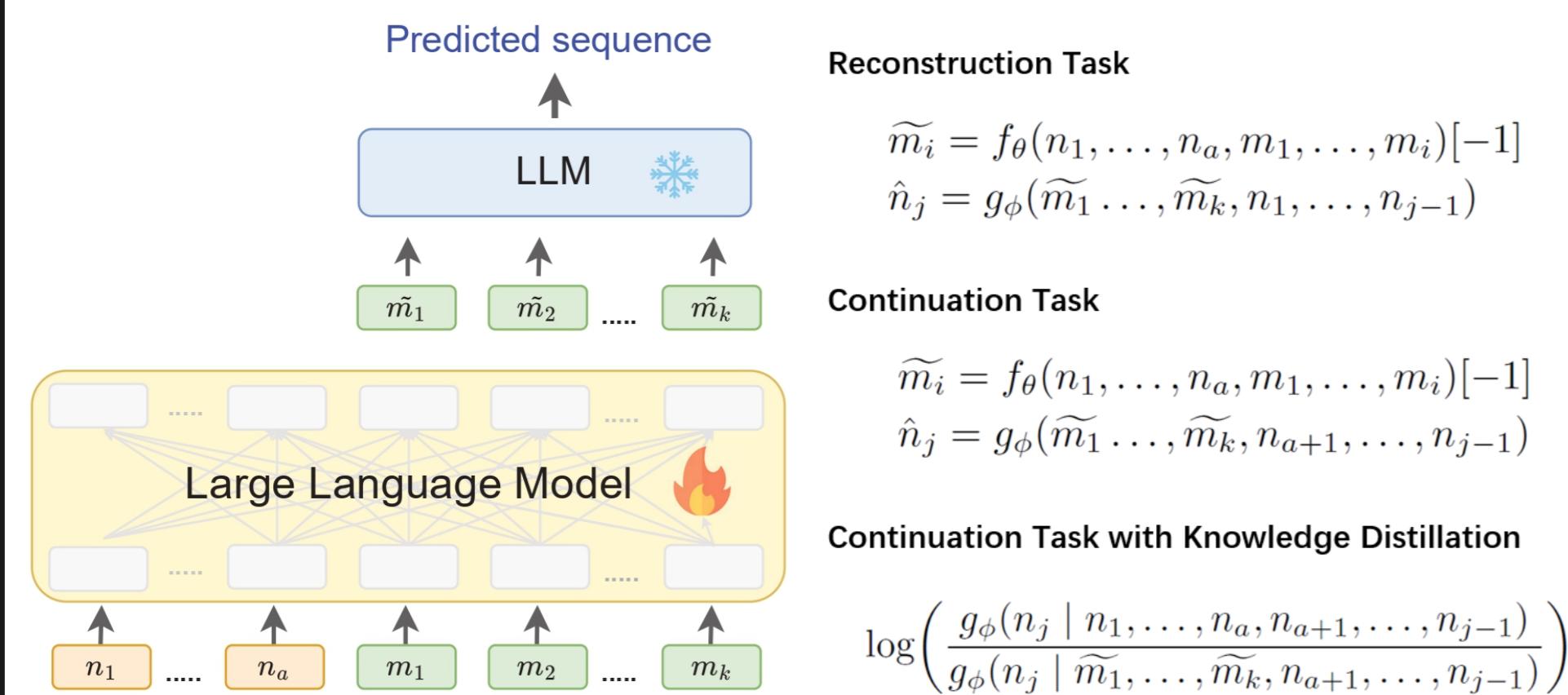
MOTIVATION



- Most LLMs are inherently **causal** and optimized for **next-token prediction**, which makes them inherently **suboptimal** for generating holistic, coherent representations of entire sequences.
- Other pretext tasks remain fundamentally **token-level** rather than **sequence-level** prediction.

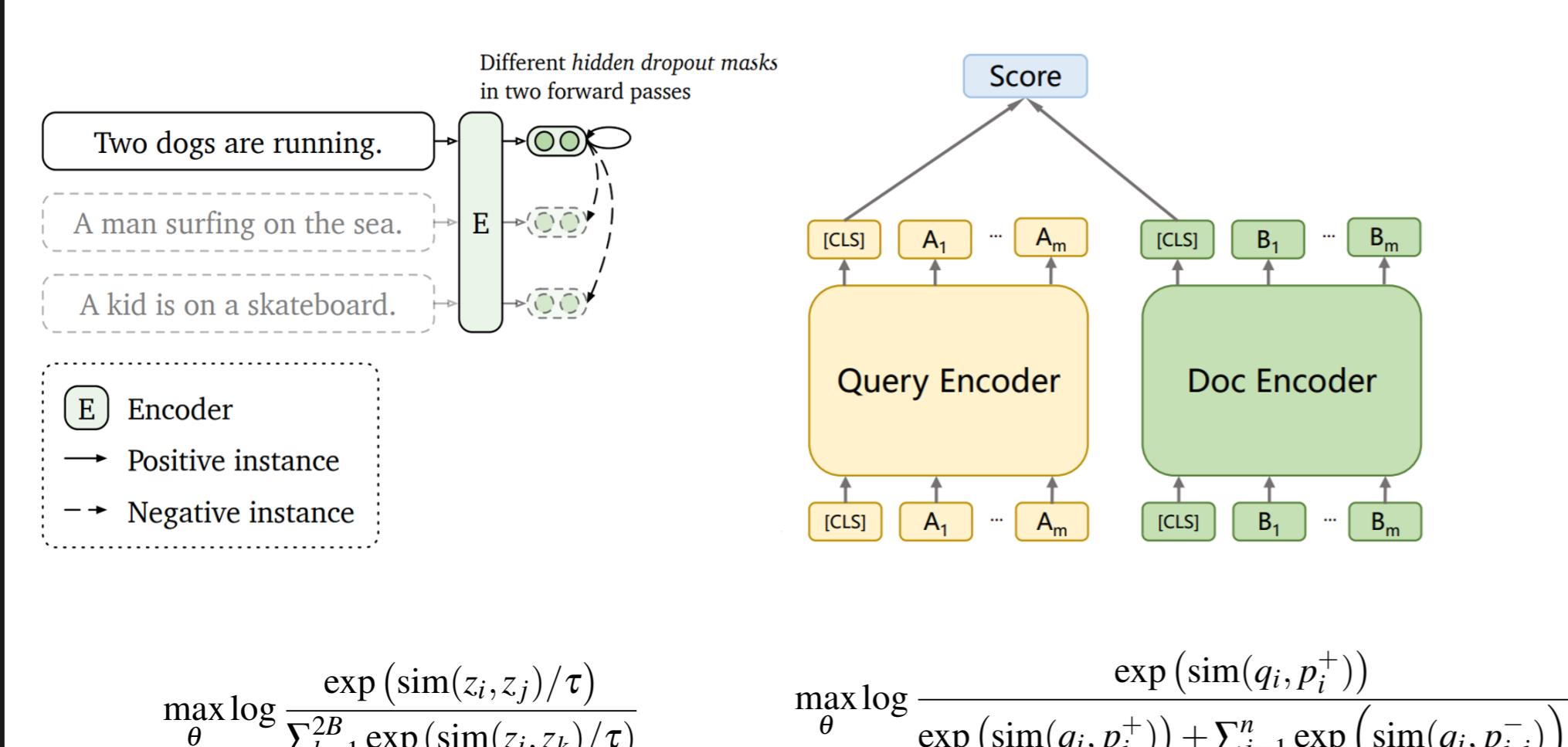
METHOD

Compression as Pretext Task



- We consider **reconstruction** and **continuation** two compression tasks.
- To further enhance encoder training, we propose a third pretext task that combines the **continuation objective with knowledge distillation**.
- Once the LLM has been adapted into the encoder f_θ , the resulting encoder can be employed to generate text embeddings through **mean pooling**.

Unsupervised Contrastive Learning and Supervised Contrastive Learning



- For UCL, we construct positive samples of a particular sentence through **dropout**, and treat other sentence samples as negative ones.
- We perform SCL based on supervised data, where relevant pairs are **manually annotated**. Negative samples are chosen following **in-batch negative sampling** and **hard-negative sampling**.
- In the UCL stage, we utilize a Wikipedia sentence subset. In the SCL stage, we utilize 1,024,000 samples from the public portions of datasets.

EXPERIMENTS

Pretext Task Experiment

Model	Training Samples	Backbone	Clustering			Retrieval			STS			Classification			Reranking			
			BioRxiv S2S	MedRxiv S2S	Twenty newsgroups Clustering	SciFact	NFCorpus	ArguAna	STS17	SICK-R	STS Benchmark	Banking77 Classification	Emotion Classification	Sprint Duplicate Questions	Stack Overflow DupQues	SciDocs RR	Avg.	
Training-free Methods & Models trained with Pretext Tasks																		
LT	0	Llama-2	15.99	17.42	15.96	14.24	57.8	55.63	45.72	68.65	29.85	47.01	32.07	58.83	33.05			
WMP	0	Llama-2	19.73	19.47	14.54	38.89	6.13	33.59	63.91	57.52	66.42	30.97	58.48	37.74	61.05	40.46		
EE	0	Llama-2	22.94	23.15	25.74	25.61	9.97	25.24	80.51	70.18	71.94	45.00	68.48	40.79	60.15	46.54		
PromptEOL	0	Llama-2	22.49	21.14	31.47	27.16	13.59	11.65	79.67	73.82	75.32	76.37	47.13	26.08	37.65	66.22	43.55	
MetaEOL	0	Llama-2	30.95	26.56	40.59	21.75	82.29	76.88	76.87	82.26	51.05	48.24	39.87	77.91	50.83			
Llama2Vec	32k	Llama-2	22.42	22.25	20.44	16.50	5.22	32.04	75.72	58.00	60.48	75.83	38.64	84.47	28.75	55.51	45.54	
Llama2Vec	32k	Llama-2	26.41	27.44	25.76	44.51	4.24	31.02	72.65	67.66	65.92	79.77	39.30	41.46	41.46	41.46	35.47	
LLM2Comp _{RC}	32k	Llama-2	6.65	13.56	8.94	17.41	1.56	14.58	64.64	54.37	41.20	73.95	36.06	76.89	36.50	54.72	35.79	
LLM2Comp _{NLL}	32k	Llama-2	30.24	27.34	37.25	11.93	3.55	24.69	70.65	64.57	63.05	80.12	39.40	72.02	43.36	78.94	46.22	
LLM2Comp _{KL}	32k	Llama-2	27.79	26.00	31.19	42.57	9.24	30.92	81.56	68.28	70.87	84.33	46.85	88.81	48.20	78.18	52.49	

- LLM2Comp_{RC} performs **only slightly better** than simple last-token pooling (LT).
- Continuation-based objectives lead to substantial improvements, making LLM2Comp_{NLL} and LLM2Comp_{KL} significantly **outperform** LLM2Vec, Llama2Vec and all training-free baselines by a large margin.
- The continuation task with knowledge distillation is **more effective** than the continuation task with NLL loss for text representation.

UCL Experiment and SCL Experiment

Model	Training Samples	Backbone	Clustering			Retrieval			STS			Classification			Reranking				
			BioRxiv S2S	MedRxiv S2S	Twenty newsgroups Clustering	SciFact	NFCorpus	ArguAna	STS17	SICK-R	STS Benchmark	Banking77 Classification	Emotion Classification	Sprint Duplicate Questions	Stack Overflow DupQues	SciDocs RR	Avg.		
Unsupervised contrastive learning (UCL)																			
LLM2Vec	160k	Llama-2	31.25	28.04	30.76	64.48	26.81	47.09	86.70	71.77	78.32	84.65	46.58	87.57	47.77	77.62	57.82		
LLM2Comp _{KL}	160k	Llama-2	32.77	28.32	38.52	59.65	33.64	31.78	73.69	79.58	86.32	84.24	48.56	94.15	51.50	80.94	58.51		
LLM2Comp _{RC}	160k	Llama-2	7.88	14.97	15.34	52.96	17.16	27.38	39.37	46.78	86.30	60.32	75.77	32.55	90.81	42.53	65.39	45.41	
LLM2Comp _{NLL}	160k	Llama-2	31.03	26.65	35.97	28.10	43.65	70.40	45.51	91.65	83.83	87.27	85.85	44.78	91.03	50.95	79.22	56.84	
Supervised contrastive learning (SCL)																			
Instructor	1.4M	GTR-XL	30.60	30.80	53.30	64.60	36.00	55.70	90.50	81.70	86.60	82.70	53.20	94.90	52.50	79.50	63.76		
ULLME	0.5M	Phi-1.5	30.46	30.18	42.95	63.41	34.54	55.06	88.49	70.49	80.81	84.24	45.83	92.78	48.61	79.29	60.51		
ULLME	0.5M	Mistral-0.2	31.48	26.95	38.52	72.86	39.37	45.93	86.30	78.21	84.57	45.02	92.20	52.56	83.47	60.56			
ULLME	0.5M	Llama-0.1	30.32	26.01	41.32	72.38	39.37	45.93	86.30	69.11	80.25	84.76	49.48	94.73	52.38	81.42	61.05		
RepLlama	0.5M	Llama-0.1	35.00	28.10	43.65	70.40	45.51	55.81	86.30	75.40	87.27	85.85	54.29	94.79	51.48	84.31	65.43		
Llama2Vec	>3M	Llama-2	30.38	28.21	45.63	75.95	37.38	49.08	66.73	68.57	71.61	77.05	46.17	95.65	45.87	77.04	58.24		
Llama2Vec	1.16M	Llama-2	34.81	31.37	51.04	77.30	40.33	56.53	90.63	83.01	88.72	88.17	51.71	96.83	51.02	84.03	66.11		
LLM2Comp _{RC} </td																			