

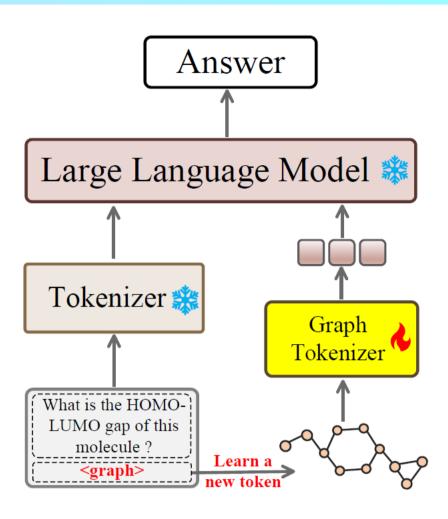
Graph2Token: Make LLMs Understand Molecule Graphs



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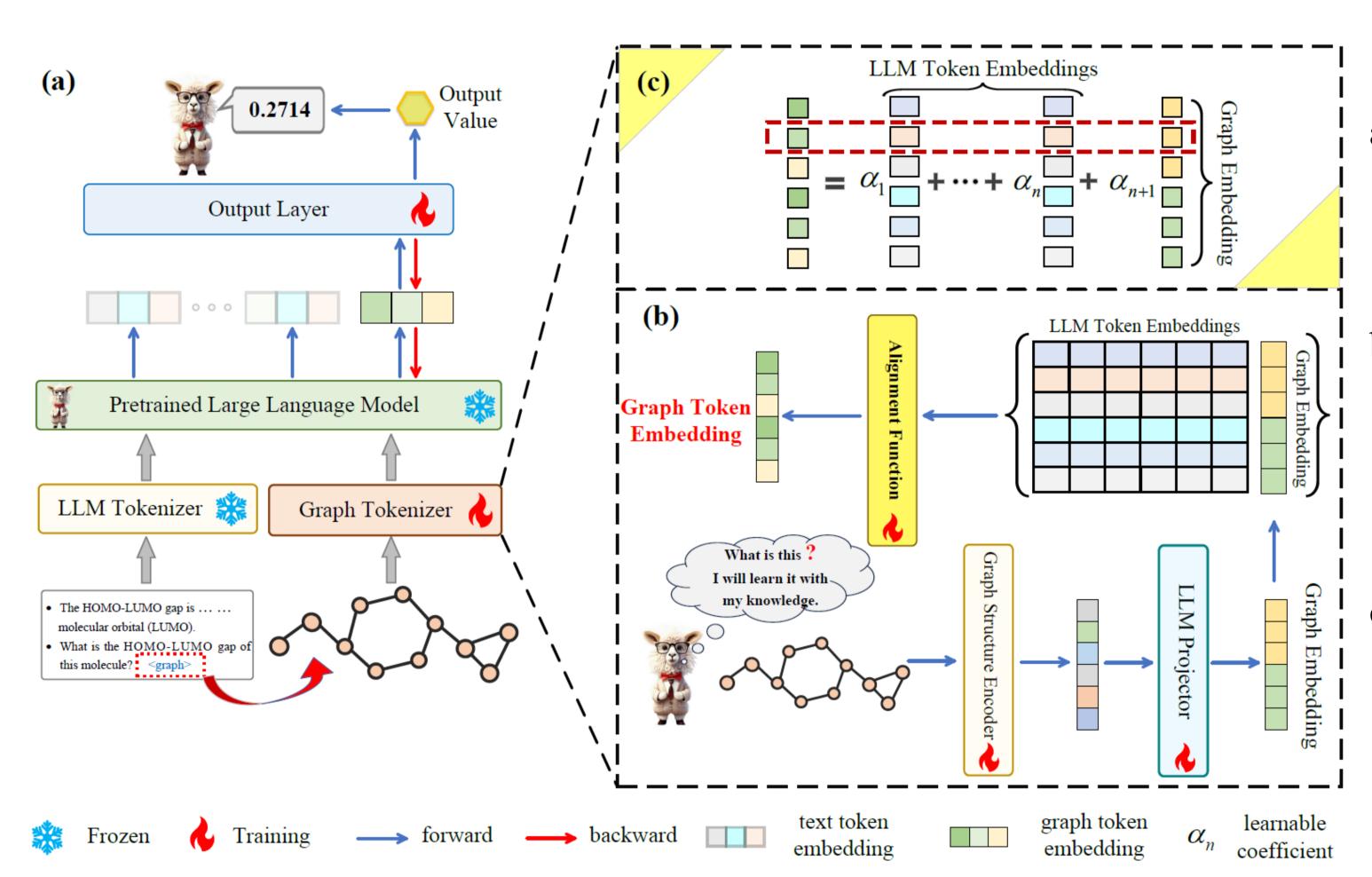
Motivation

- > Large language models (LLMs) excel at various text-related tasks.
- > It is still challenging for LLMs to process molecular graph data.
- > Graph2Token, an efficient solution that aligns a graph token to LLM tokens.



Graph2Token

Aligning a graph token with the LLM token vocabulary



- a) The architecture of Graph2Token with frozen LLM tokenizer and trainable graph tokenizer.
- b) The trainable graph tokenizer learns the unknown graph token representation using LLM token vocabulary.
- c) Alignment function utilizes a learnable combination of tokens pre-trained by LLM to represent the graph tokens.

Graph2Token

64.7

73.2

68.5

70.6

69.5

74.6

69.7

71.2

Finetune and few-shot learning performance on molecular datasets

Method Type	Method	$BBBP \uparrow$	BACE ↑	$HIV\uparrow$	TOX21 ↑	Avg↑
Supervised Learning	rning GIN		76.8	76.5	73.9	73.8
	GT	68.7	77.2	74.2	75.5	73.9
Graph Pretrain Finetuning	GraphMVP-C	72.4	81.2	77.0	74.4	76.3
	Mole-BERT	70.8	79.3	76.0	75.9	75.5
	MolFM	<u>72.9</u>	83.9	<u>78.8</u>	<u>77.2</u>	<u>78.2</u>
	SimSGT		83.6	77.7	75.7	77.3
LLM-Based Tuning Llama-2-7B-		65.6	74.8	62.3	-	67.6
	Vicuna-v1.3-7B	60.1	68.3	58.1	-	62.6
	MolCA-S	70.8	79.3	-	76.0	75.4
	MolCA-GS	70.0	79.8	-	77.2	75.7
	InstructMol-G	64.0	85.9	74.0	-	74.6
	InstructMol-GS	70.0	82.3	68.9	-	73.7
	Graph2Token	73.5	<u>85.0</u>	79.4	79.2	79.3

•	Few-sho	t lear	ning	using	5%	and	10%
	training	data	on	differe	ent	mole	cular
	datasets.						

• Results (ROC-AUC) of finetune learning on molecular classification tasks on different datasets compared with LLM-based methods and graph learning methods.



Dataset

BBBP

BACE

HIV

TOX21

BBBP

BACE

HIV

TOX21

Ratio

5%

10%



GCN

64.4

65.1

62.7

58.4

67.0

64.6

60.0

68.4

GIN

61.8

64.4

66.2

62.6

66.9

68.1

66.9

66.7