

## Introduction

Each database running a different workload, demands different resources and database configuration settings to achieve optimal performance, which prompts us to study workload features in detail.

We define a database workload as

$$W = \{(p_1, \theta_1), (p_2, \theta_2), \dots, (p_m, \theta_m)\},$$

where  $p_i$  is the database query-plan, and  $\theta_i$  is a normalized weight of importance of  $p_i$  in workload  $W$ . For understanding workloads comprehensively it is necessary to perform feature engineering on query plans.

## Key Contributions

- We propose query plan encoder models capturing structure and computational performance resource requisites as distributed feature representations.
- We keep structure, and computational performance representation separate that enables downstream tasks to weigh each representation independently in their model.
- We propose a taxonomy for operator types for learning diverse structure of query plans with self-attentive transformers.
- We find performance of query plans are best characterized by encoders when plan task nodes are classified under scan, join, sort and aggregate; each having an encoder of its type.
- Latency prediction and query classification downstream tasks performing well with our pretrained encoders suggests efficacy of our modeling strategy.
- In depth domain adaptation evaluation and ablation studies on various datasets signifies pretrained encoders adapts to new domain quickly, whereas encoders trained from scratch overfits.
- In this work, we open-sourced an automated workload execution tool for cloud, a crowd-sourced plan dataset and revised two spatial benchmarks.

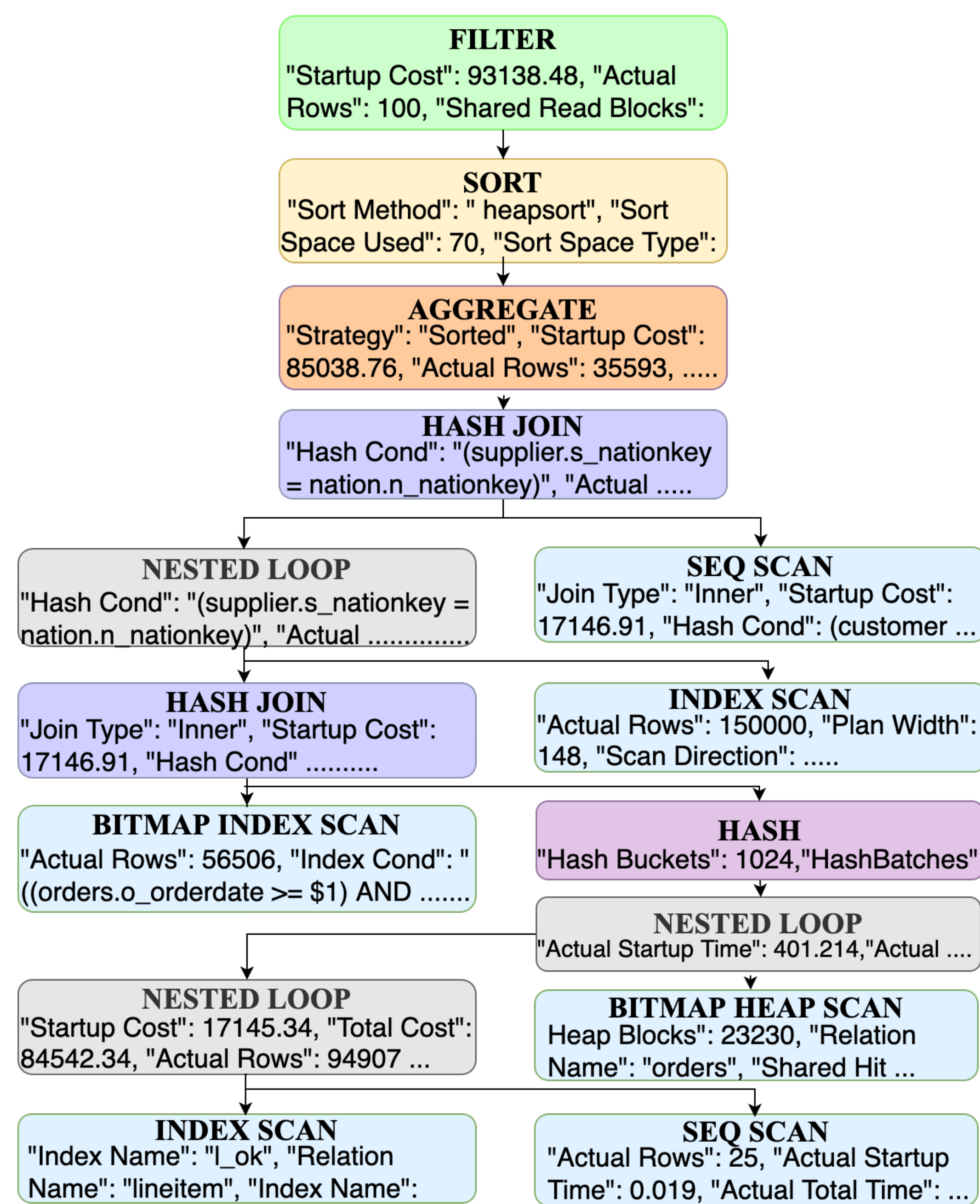


Fig 1. An example of query plan tree with different types of task/operators nodes. It is to note that many properties are associated with each task node. This query plan is from TPC-H Query Template 5.

## Plan Encoders

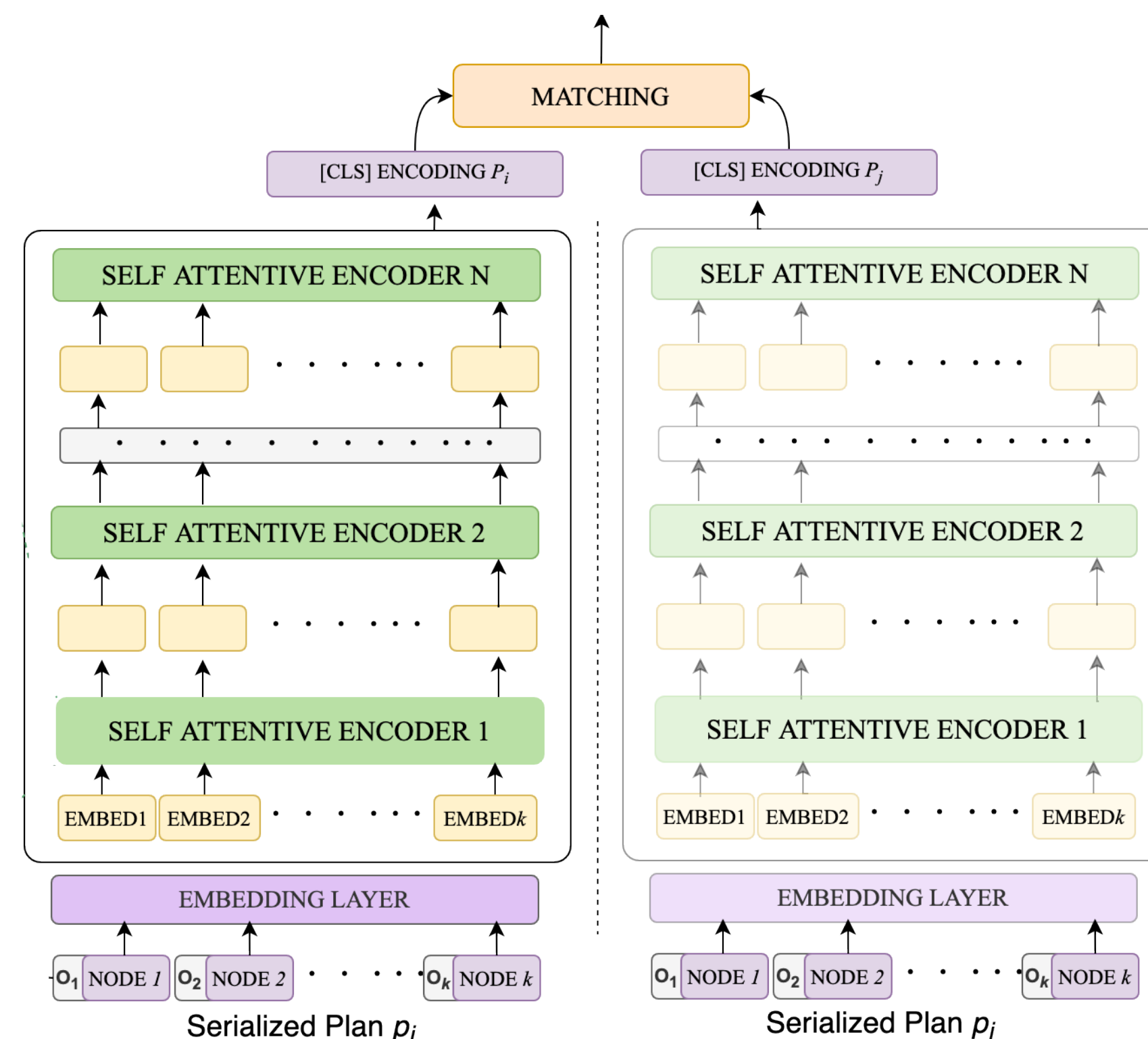


Fig 2. Structure Plan Encoder Modeling.

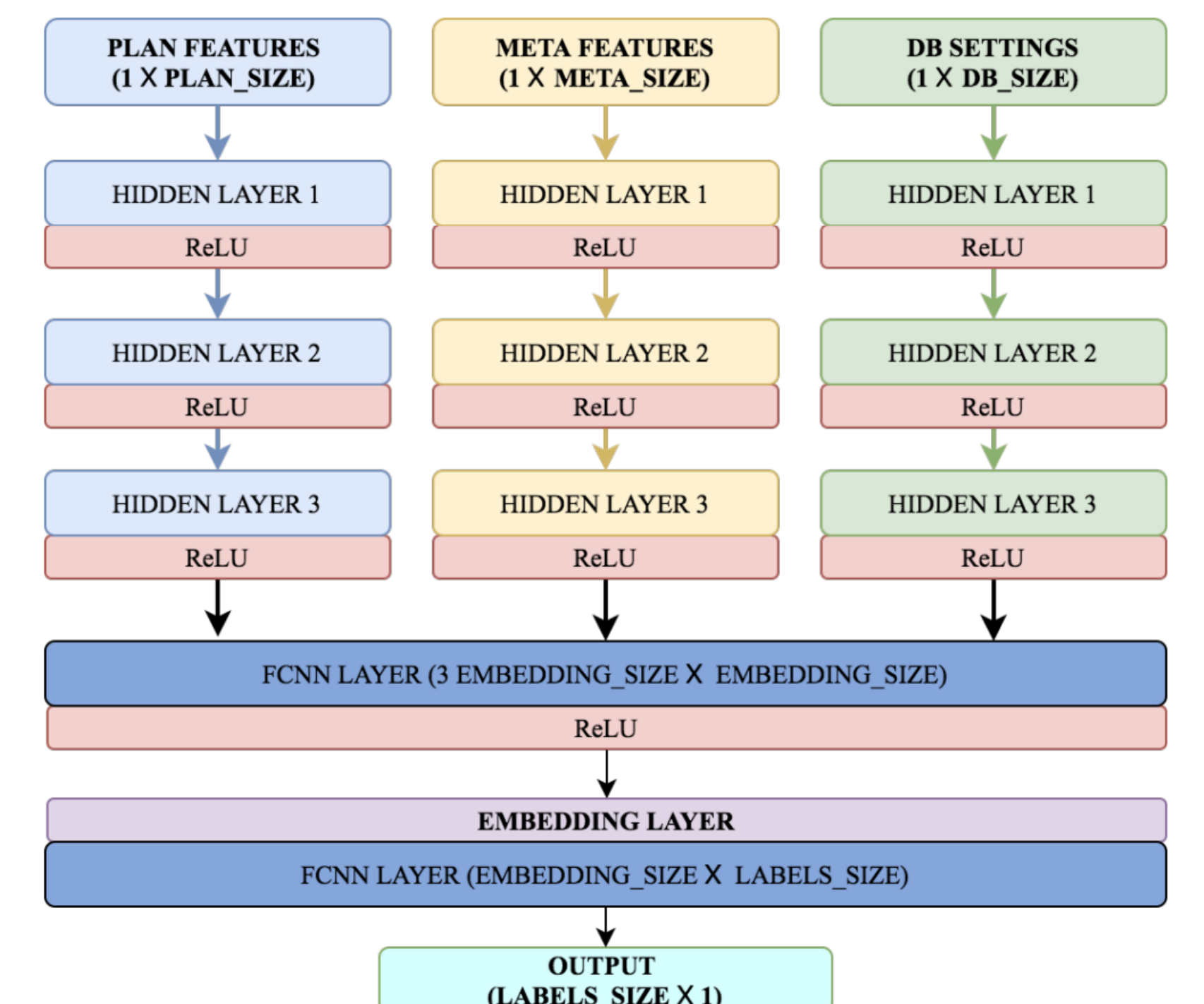


Fig 3. Computational Performance Encoder Modeling.

## Downstream Task Modeling

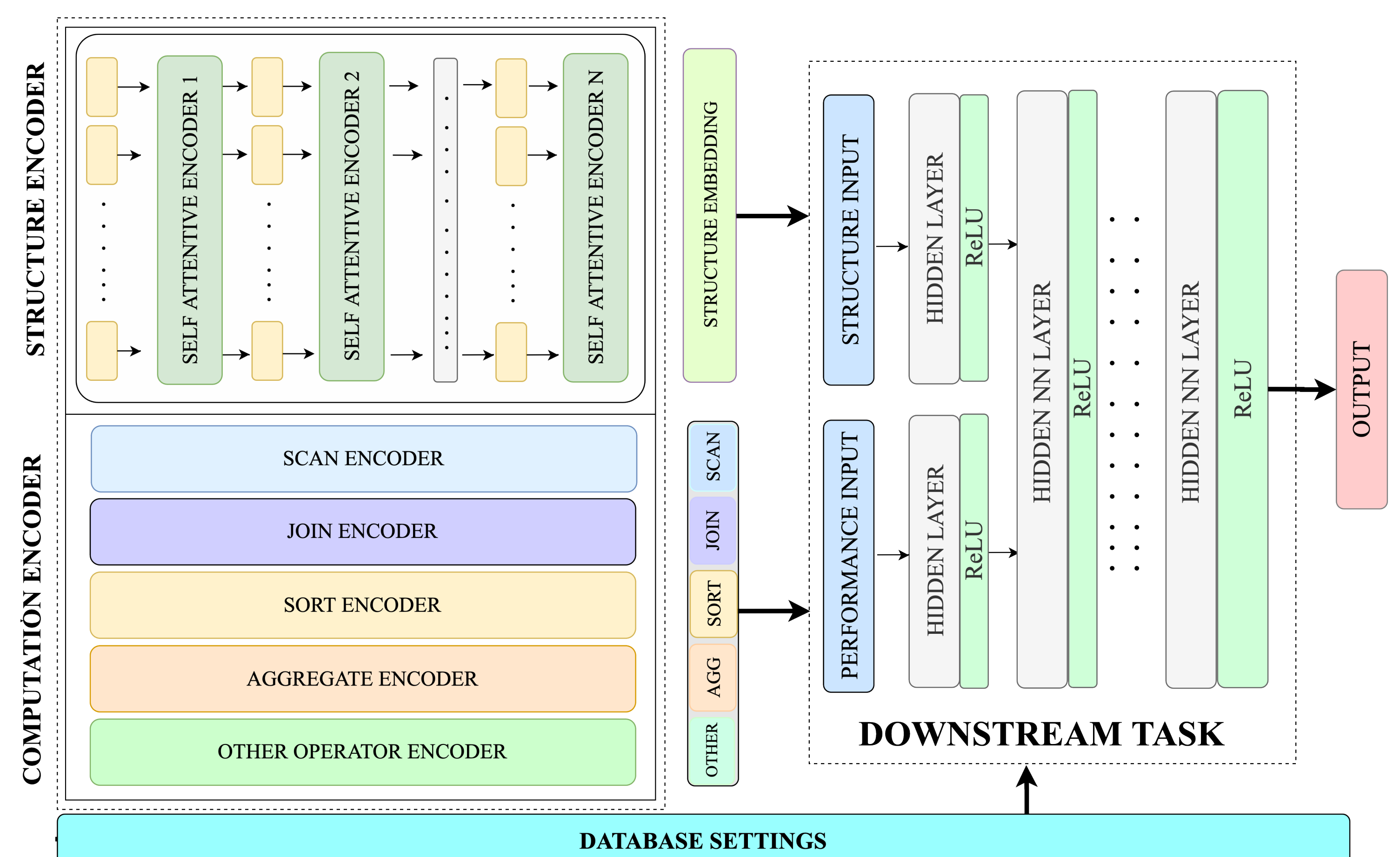


Fig 4. A bird-view architecture diagram, showing the role of plan encoders for downstream tasks. For example, latency prediction and query classification tasks.

## Results

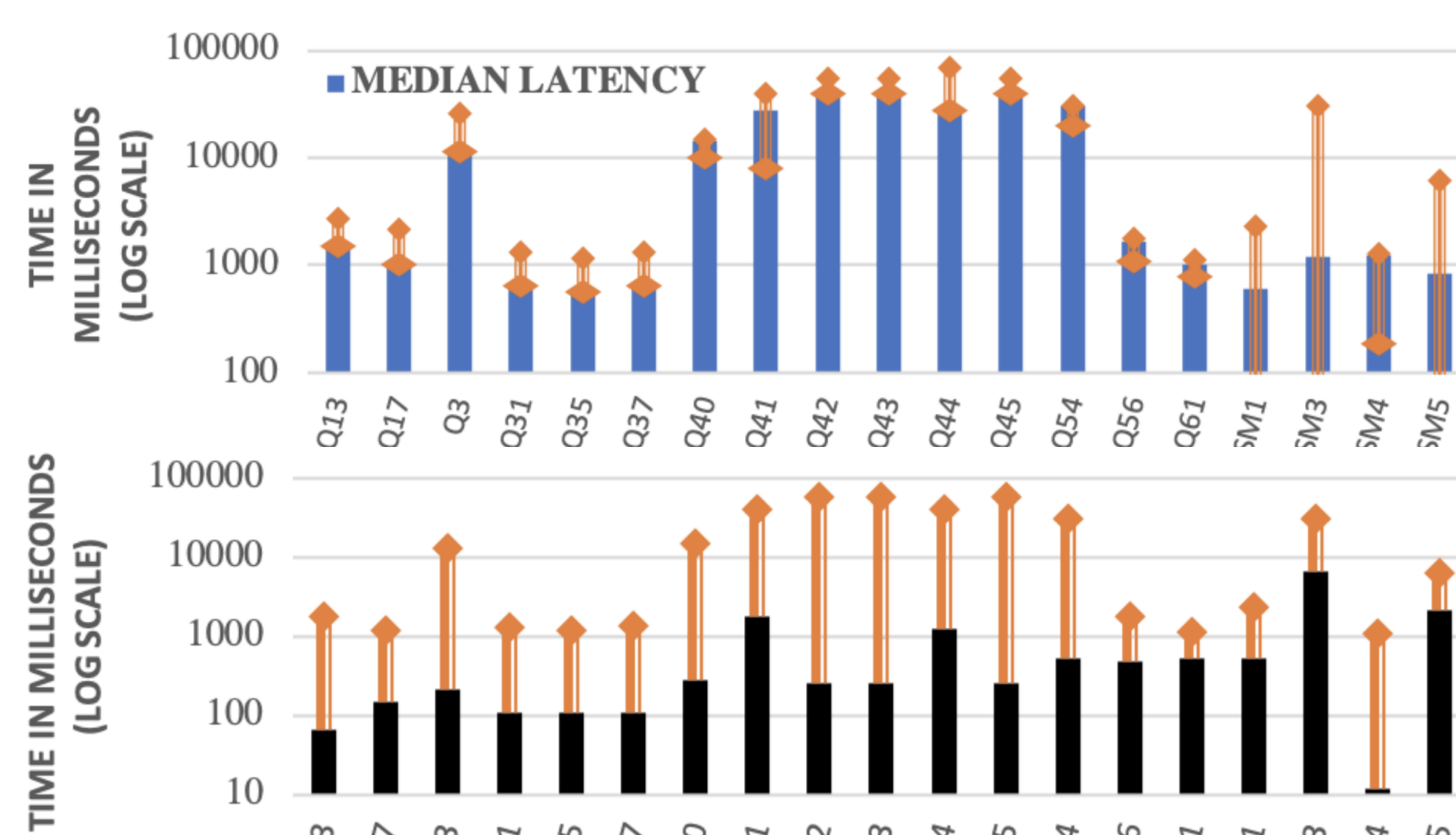


Fig 5. Blue bars are median query latency, Orange lines are 5th-95th percentile range variations, and mean abs. error marked with black bar for spatial queries. A smaller black bar on a larger orange-line bar means better results.

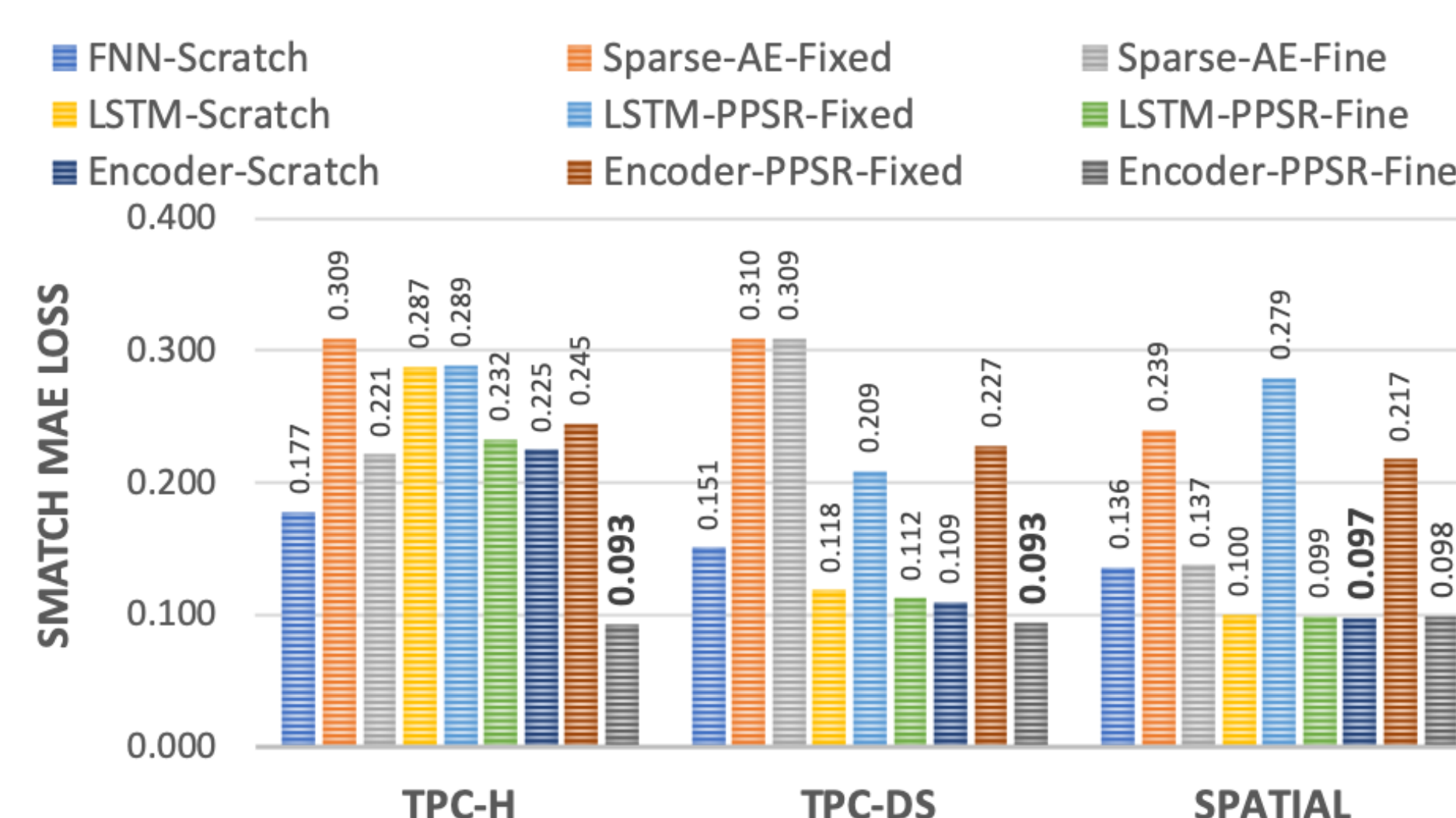


Fig 6. Results of structure encoder domain adaptation analysis on TPC-H, TPC-DS, and SPATIAL datasets. Notations: Scratch is Untrained encoder weights initialized; Fixed is Pretrained encoder weights freeze. Fine is Pretrained+Finetuned Encoder.

$$R(q) = \max\left(\frac{\text{predicted}(q)}{\text{original}(q)}, \frac{\text{original}(q)}{\text{predicted}(q)}\right)$$

Models	$R \leq 1.5$	$1.5 < R \leq 2.0$	$R > 2.0$
TAM [4]	51%	22%	27%
SVF [5]	68%	15%	17%
RBF [6]	85%	6%	9%
QPPNet [7]	89%	7%	4%
Plan Encoder	<b>91%</b>	7%	2%

Table 1. Percentage of queries from TPC-DS SF-100 testset binned based on  $R$ -factor for all the models in evaluations. Pretrained Plan Encoder performed well with 91% queries within  $1.5R$  and only 2% queries above  $2.0R$ .

Models	Development		Test	
	template	cluster	template	cluster
Structure only	0.2452	0.4670	0.1946	0.3847
Performance only	0.1645	0.2973	0.0977	0.1769
Both encoders	<b>0.2783</b>	<b>0.5573</b>	<b>0.2518</b>	<b>0.4647</b>
Both encoders 10% data	0.2000	0.4927	0.151	0.334
Both encoders 30% data	0.2555	0.5228	0.1843	0.3855

Table 2. F1-scores of models for template and cluster query classification task on development and test dataset.



<https://linkmix.co/11389156>  
Scan this QR Code for open-source resources.