

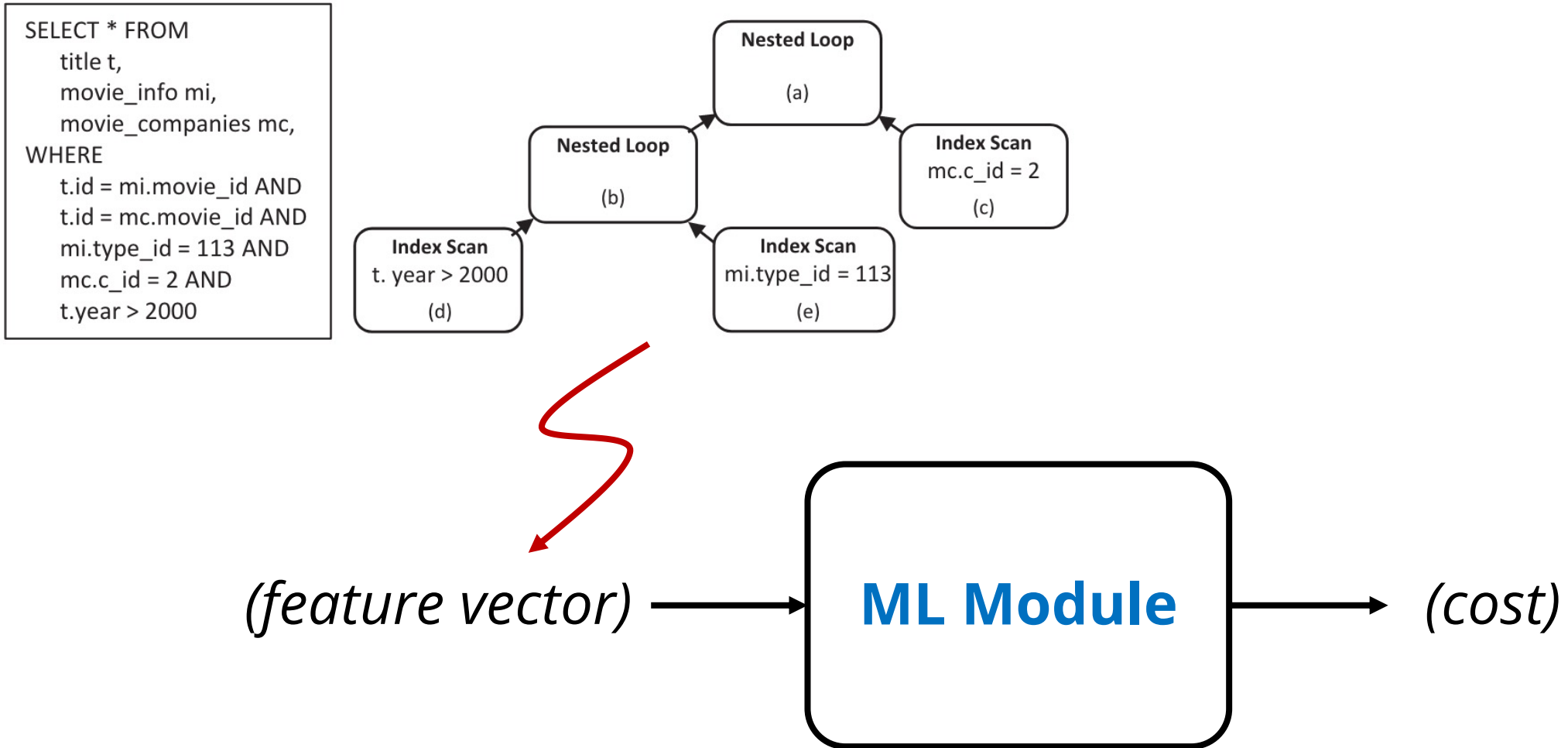
Spring25 CS598YP

15.2: QueryFormer

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Cost estimation as ML problem



Previous approaches are less effective

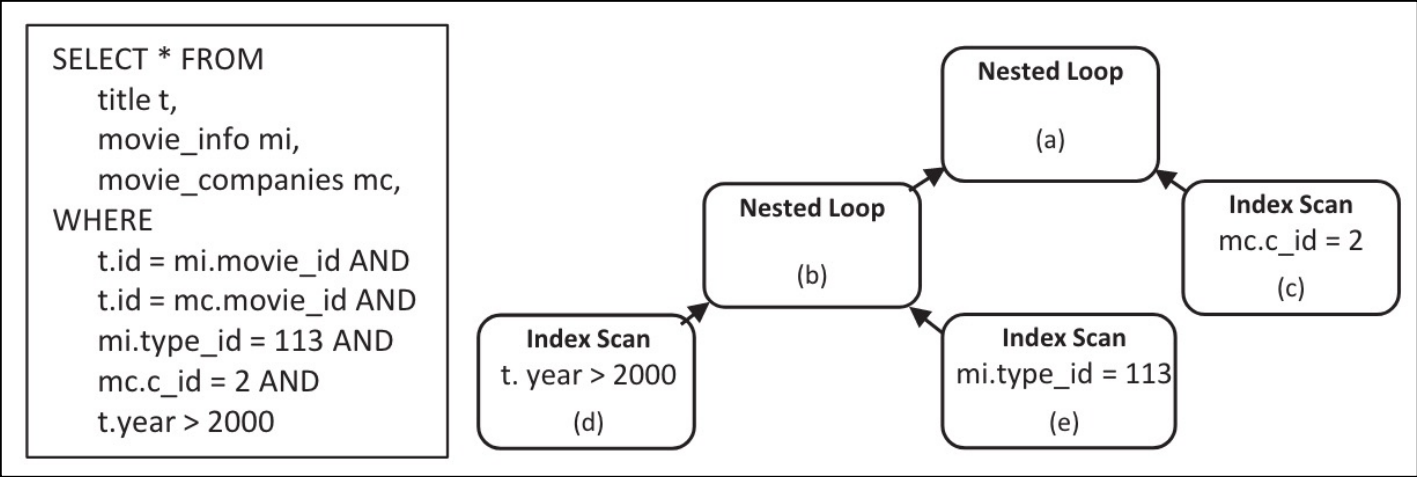
Table 1: Summary of existing solutions to query plan representation.

Category	Paper	Task	Parent-Children Dependency	Long Path Information Flow	Database Statistics	Training Difficulty
Flattened	AVGDL [38]	View Selection	No	Yes	NA	Hard
Tree-RNN	RTOS [36]	Join Order Selection	Yes	Yes	NA	Hard
	E2E-Cost [30]	Cost, Cardinality	Yes	Yes	Sample	Hard
	Plan-Cost [19]	Cost Estimation	Yes	Yes	Estimated card, cost	Hard
Tree-CNN	NEO [17]	Optimization	Yes	No	Estimated card	Easy
	BAO [16]	Optimization	Yes	No	Estimated card, cost	Easy
	Prestroid [39]	Cost Estimation	Yes	No	NA	Easy
Feature Vectors	ReJOIN [18]	Join Order Selection	No	No	NA	Easy
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Transformer	QueryFormer (Ours)	All	Yes	Yes	Sample, Histogram	Easy

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flattened:

(e)

(d)

(b)

(c)

(a)

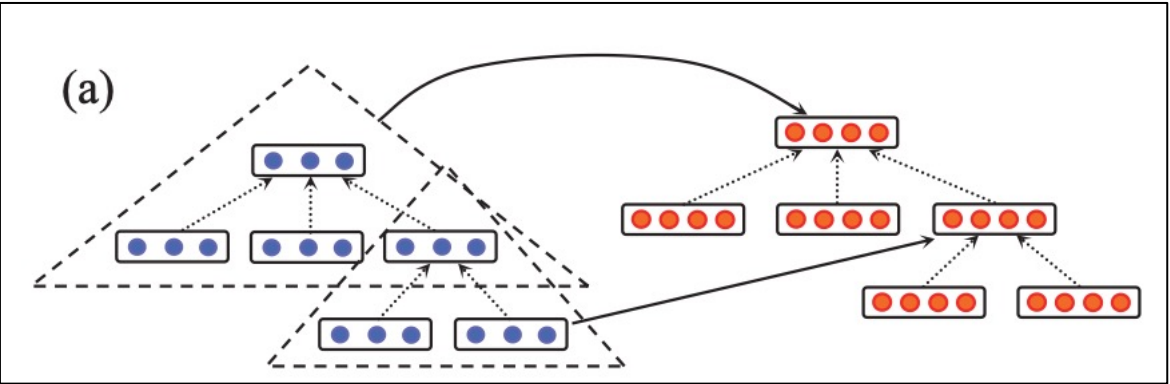
cannot capture dependency

Previous approaches are less effective

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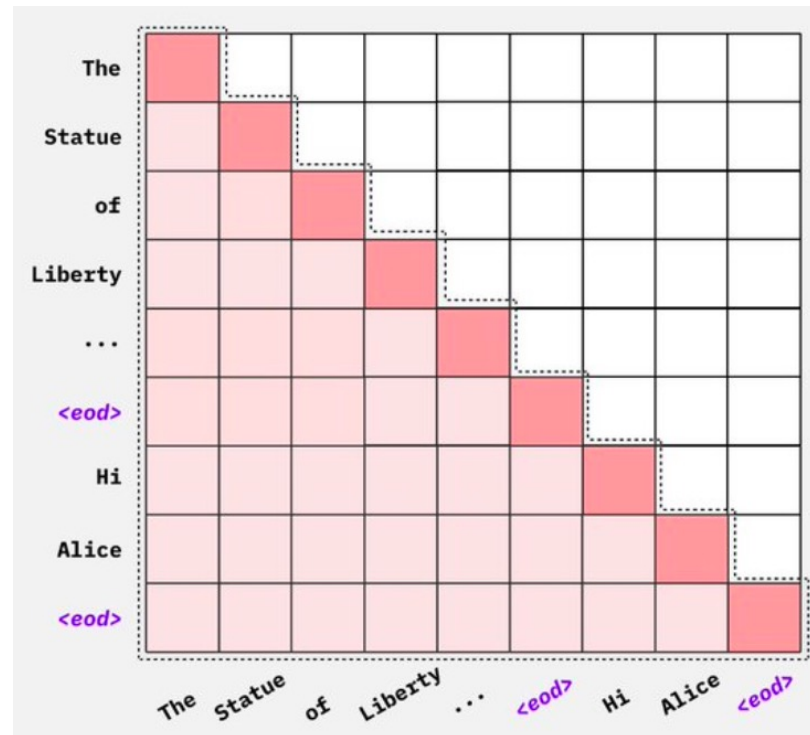
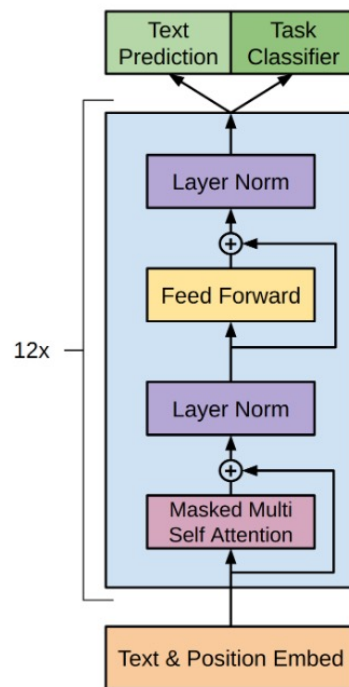
CNN



cannot capture long distance

How can we adapt Transformer / Attention?

GPT's Attention models $P(\text{new token} \mid \text{all previous tokens})$



We can manipulate this attention via masking

QueryFormer Architecture

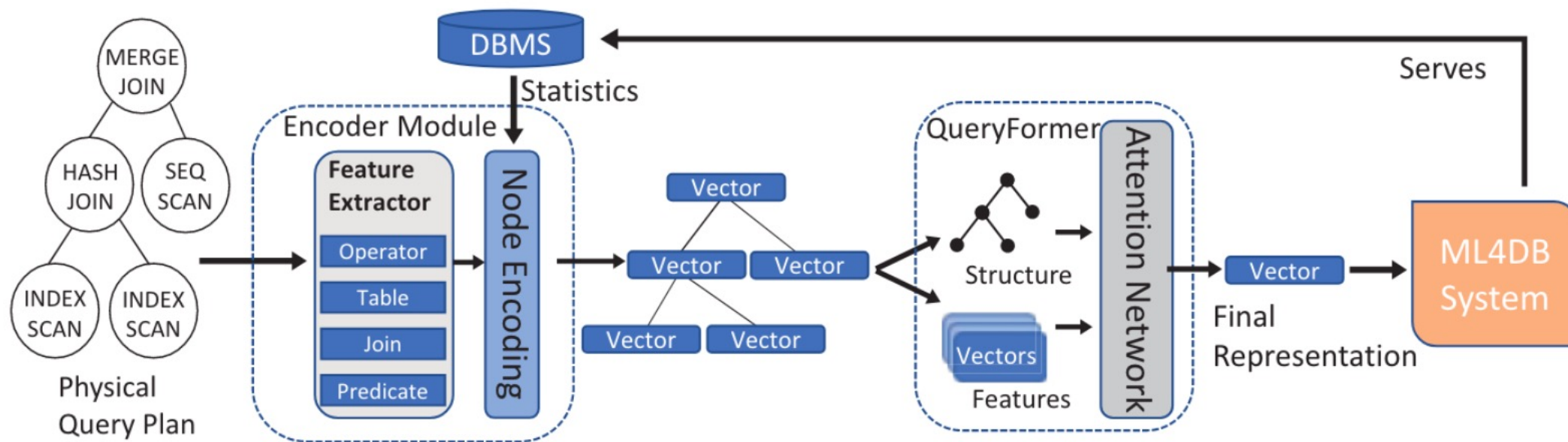


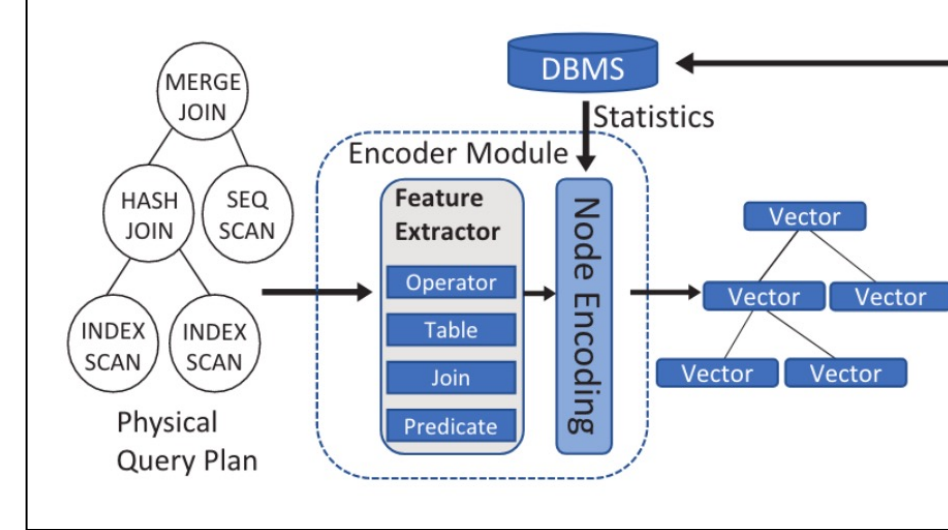
Figure 2: System overview.

Encoder: Node -> Feature Vector

Learned embedding for

- operator: merge join, index scan
- predicate: $t.year > 2000$
- table
- join condition
- per-table statistics: histogram and samples

Similar to learned embedding inside the Transformer architecture

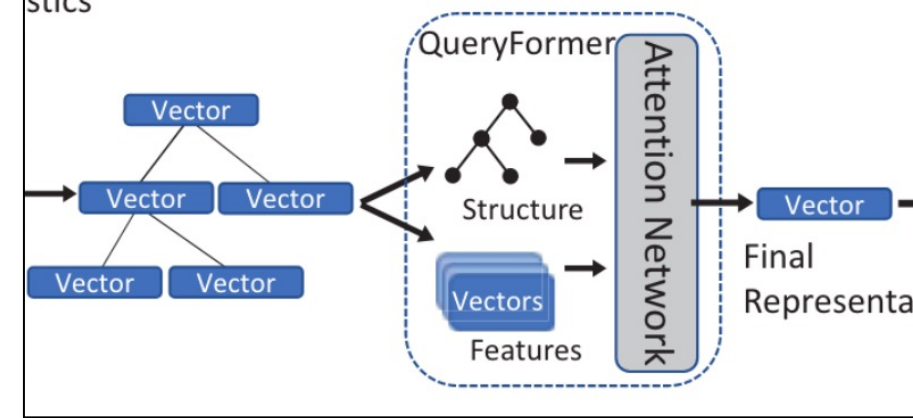


QueryFormer: Tree -> Vector

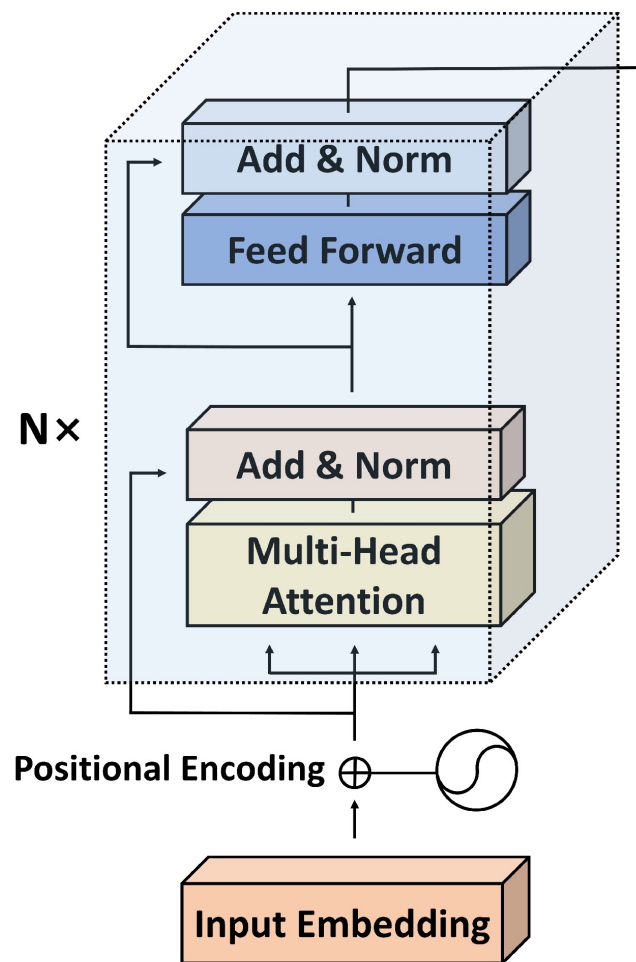
Tree-structured Transformer

- Height Encoding
- Tree-biased Attention

Aggregate nodes into a vector



Bert vs QueryFormer



BERT

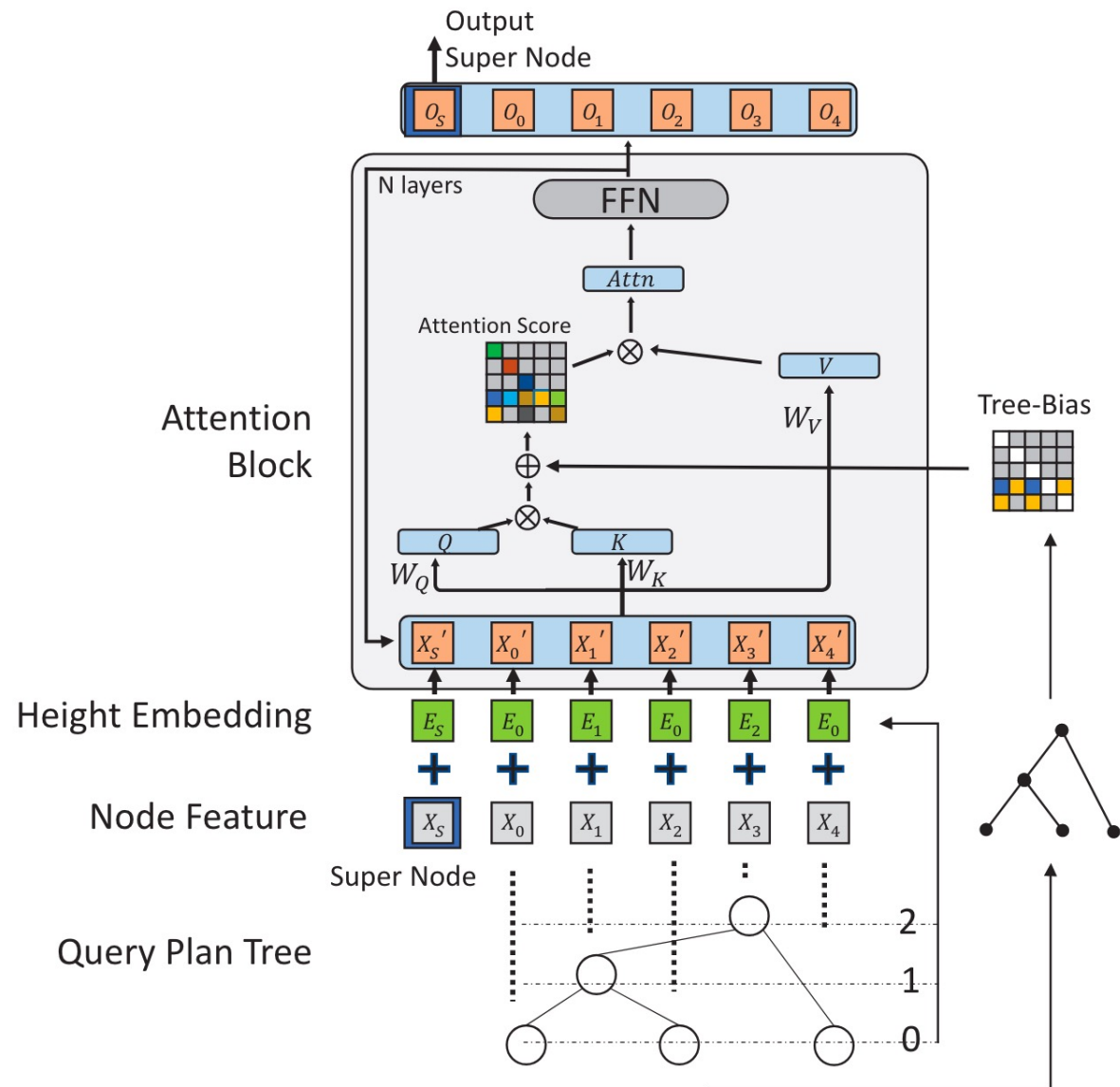
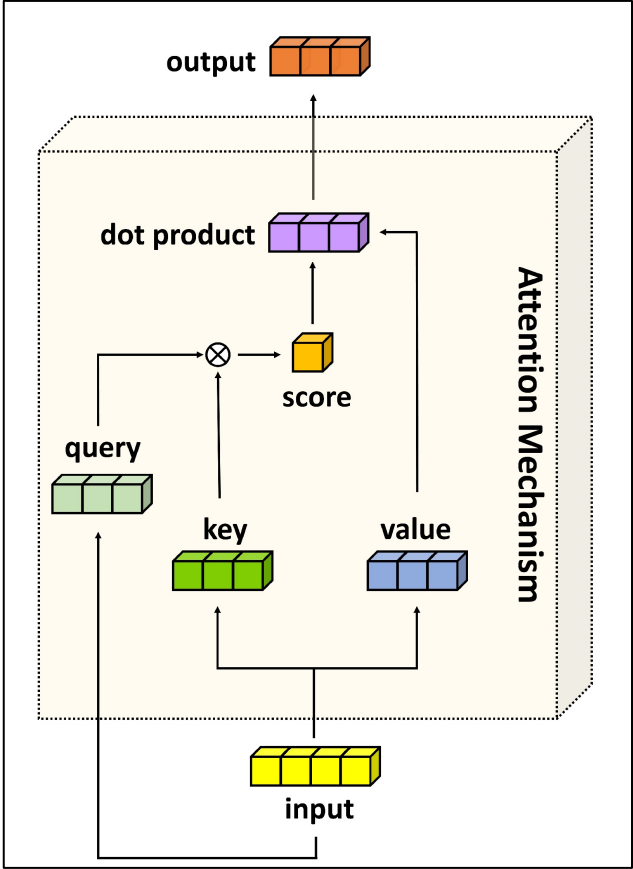
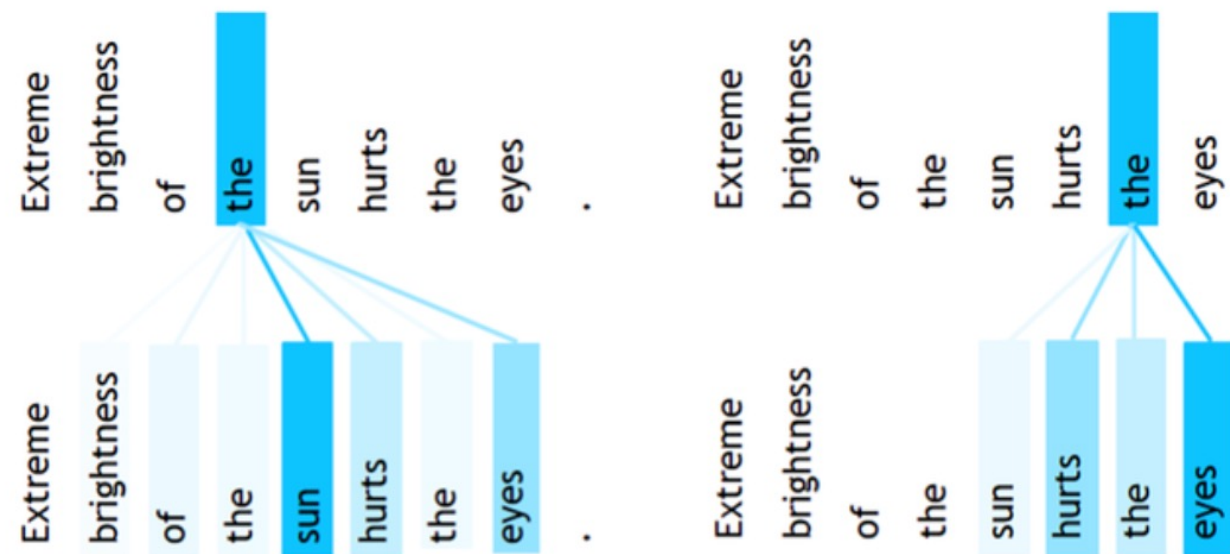
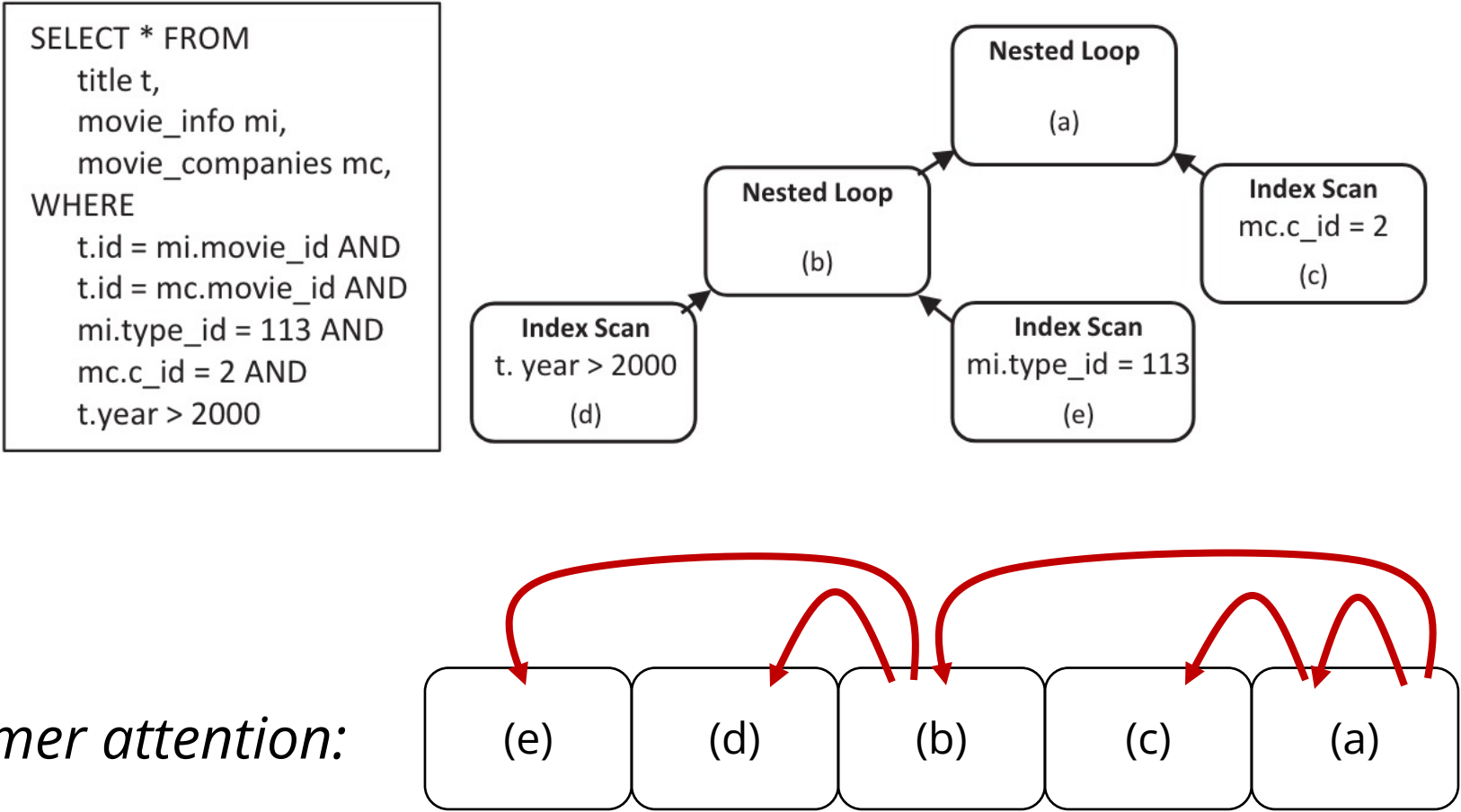


Figure 3: QueryFormer architecture.

Self-Attention in Bert / Transformer



QueryFormer: Tree-biased Attention



Summary

- **The QueryFormer paper** adapts Transformer to cost estimation
- **Encoder**: An individual node -> a vector
- **QueryFormer**: A tree of vector -> final vector (-> cost estimation)
- *Tree-biased attention* controls information flow

Questions?