

Berkeley Optimizer: Learning a Query Optimizer with Deep RL

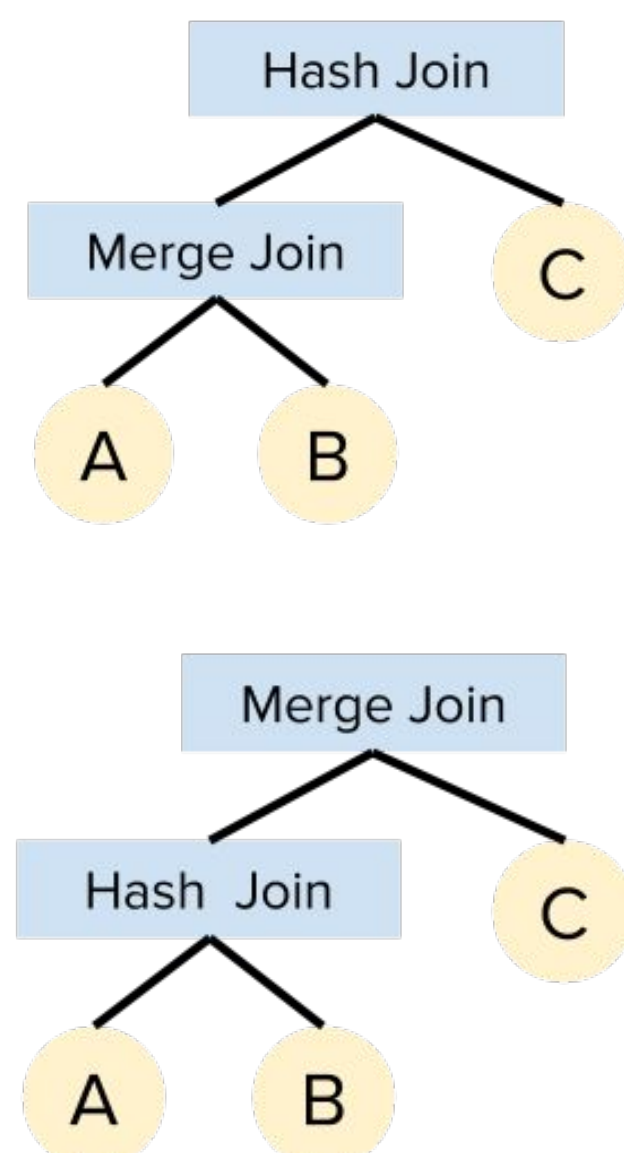
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Query → Execution Plan

Query

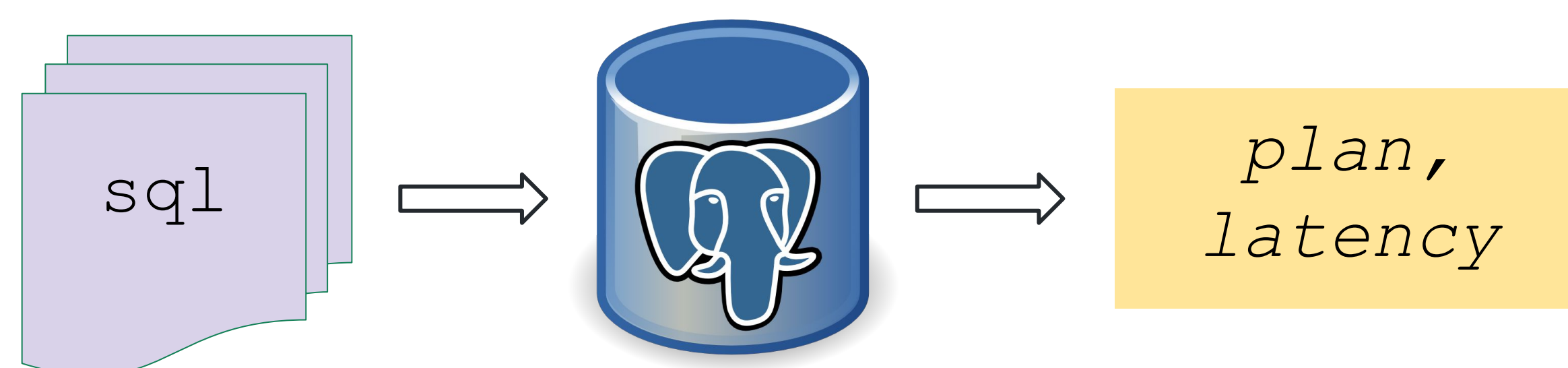
```
SELECT MIN(chn.name), MIN(t.title)
FROM char_name AS chn, title AS t
WHERE t.production_year > 1990
AND t.id = 4
AND chn.id = 9;
```

Plan



Query execution plan space is exponentially large and often relies on human-engineered cost models to generate the best plan.

Expert Bootstrapping



Deep reinforcement learning agent learns an initial policy π_0 from a human-engineered (expert) model.

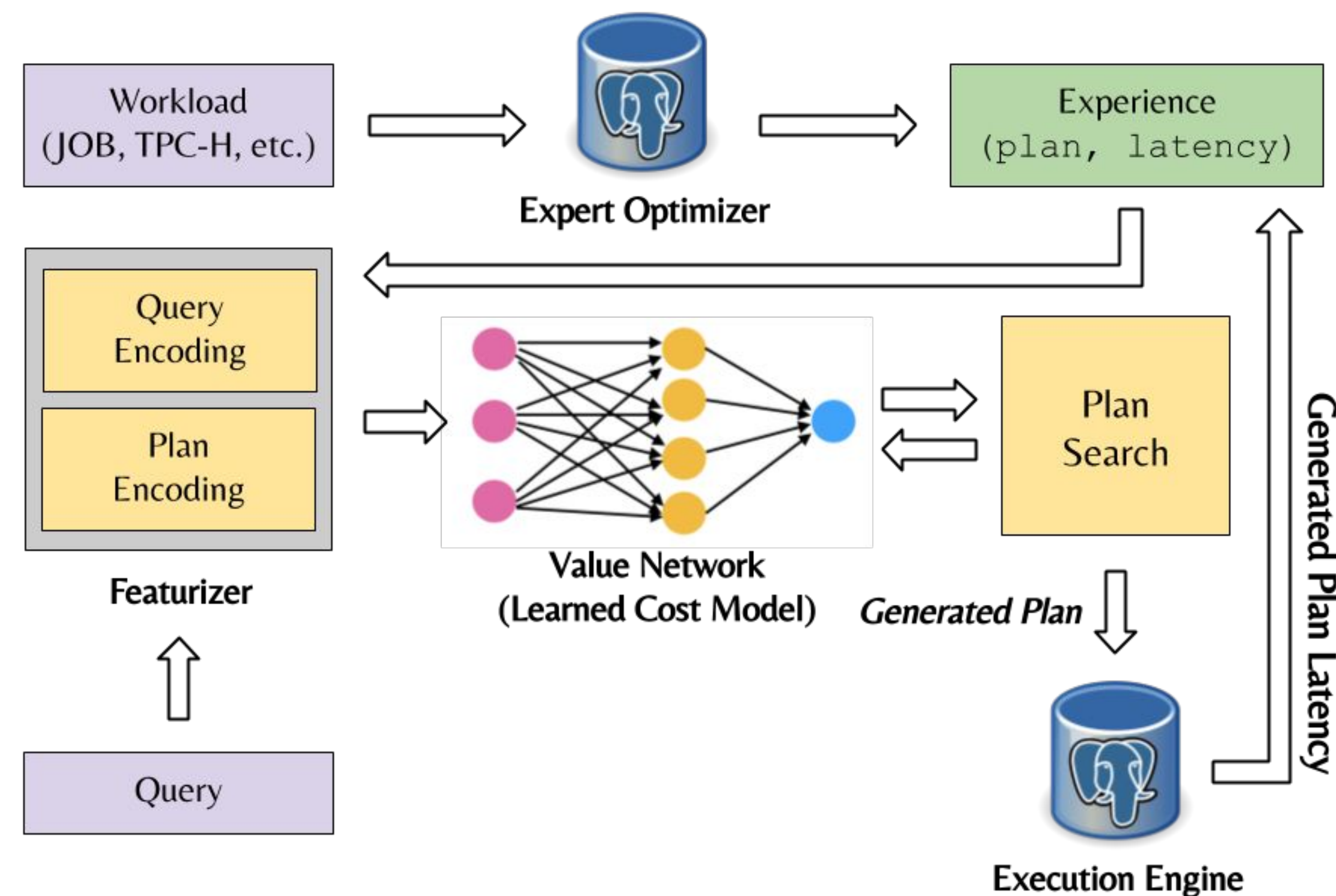
Why is this necessary?

Executing poorly planned queries can take hours to complete.

Value Iteration

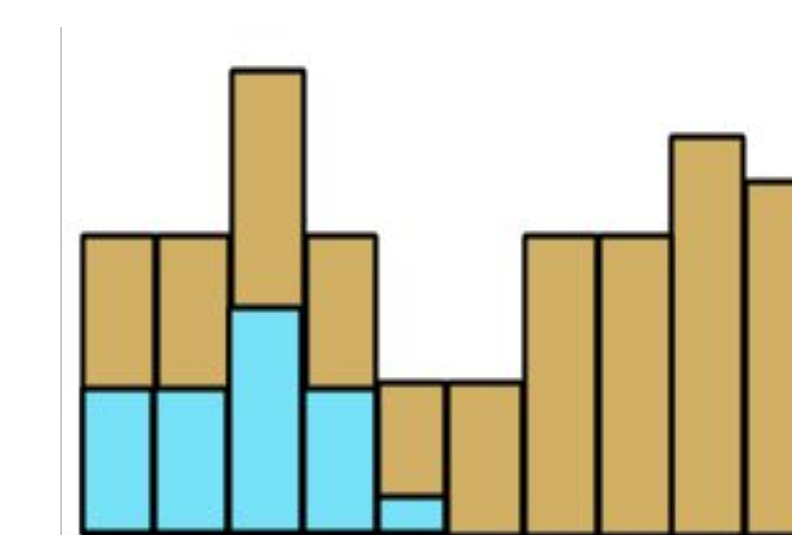
Use π_0 to learn an optimal policy through retraining agent based on generated plans + latency.

System Architecture

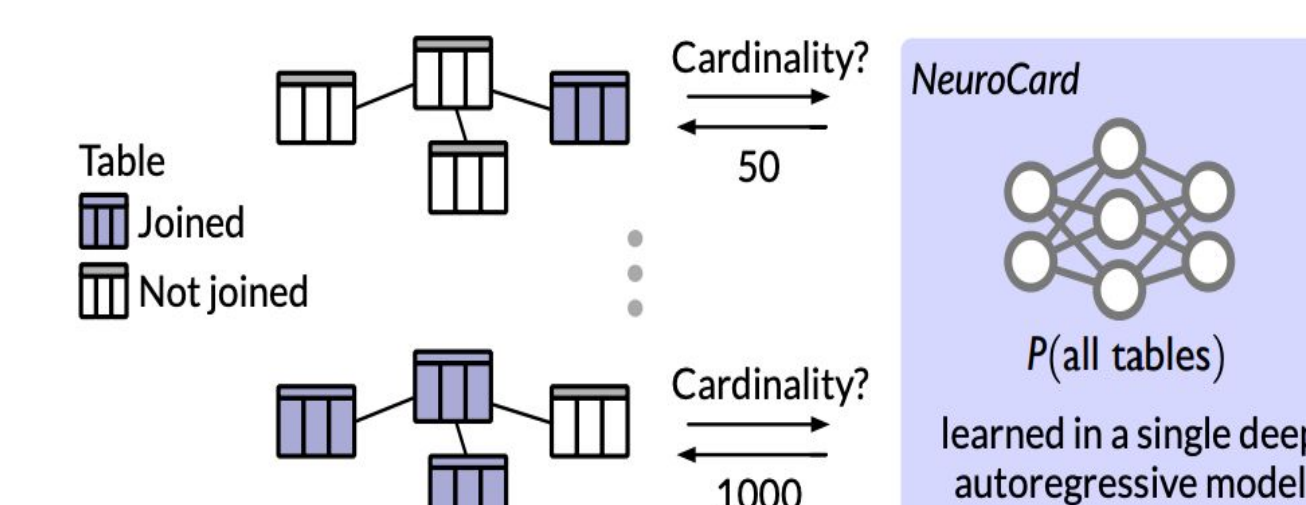


Query Encoding

Flexibility of system allows for novel improvements to featurization and cost model.



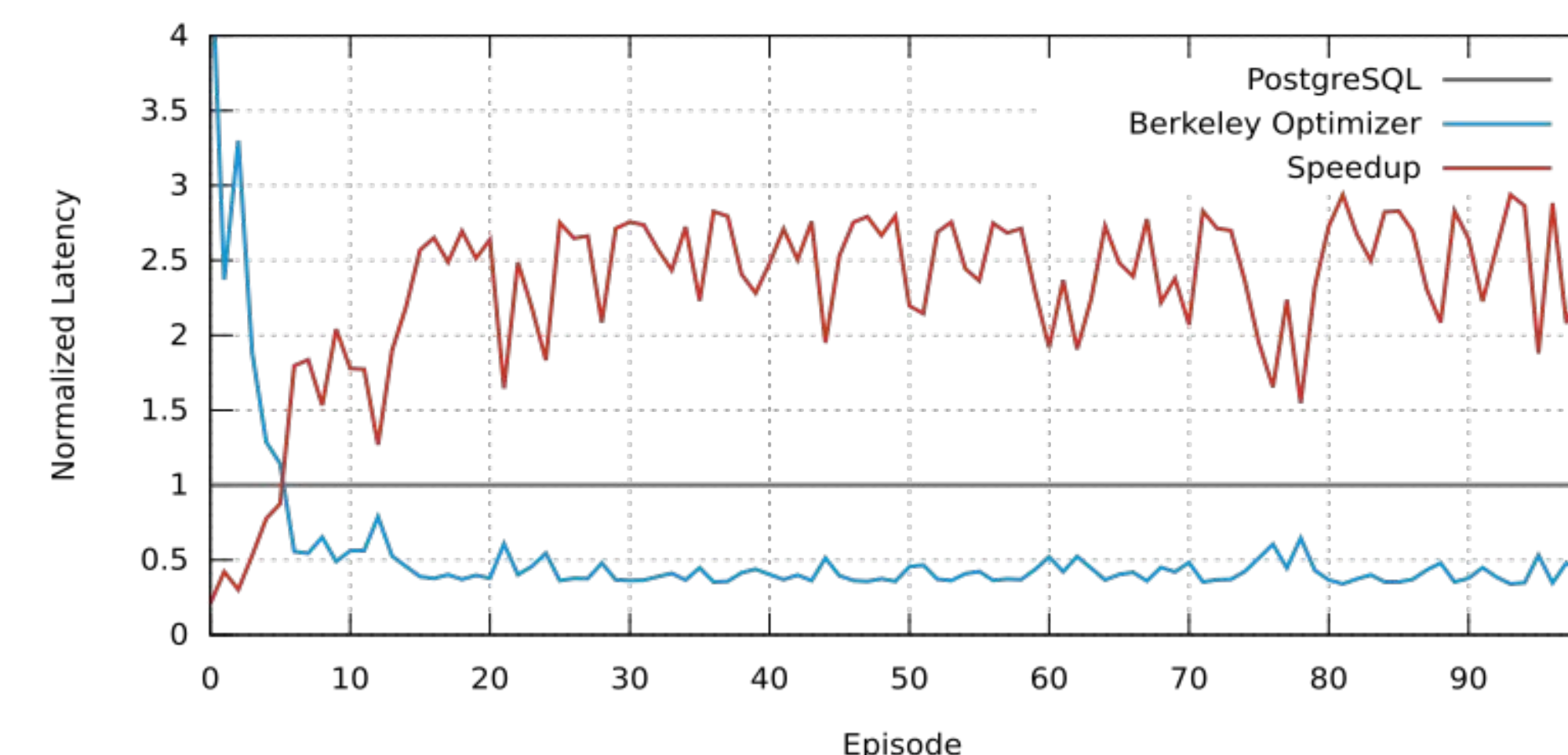
Histogram-based Selectivity Estimation



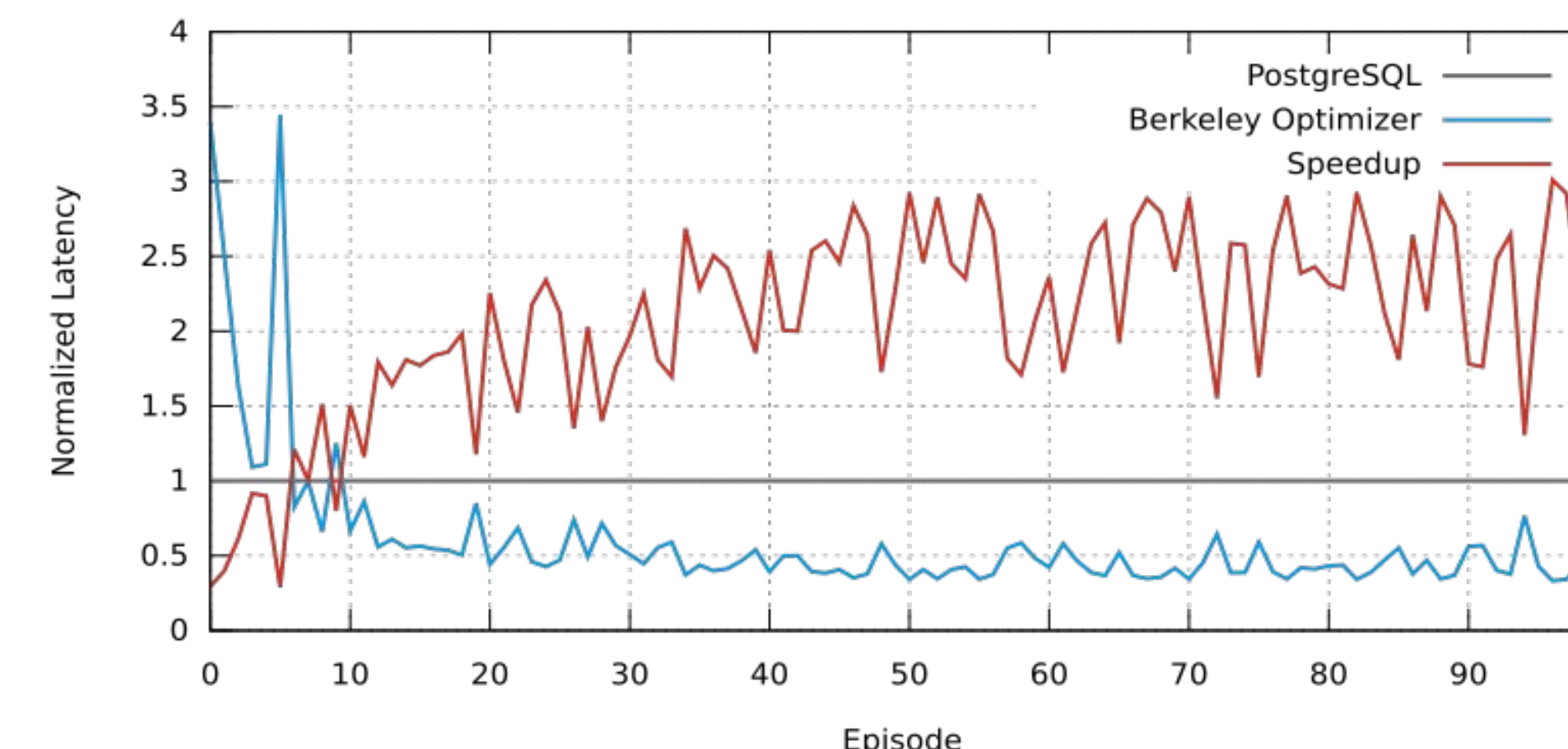
NeuroCard
(Yang et al., 2020)

Evaluation

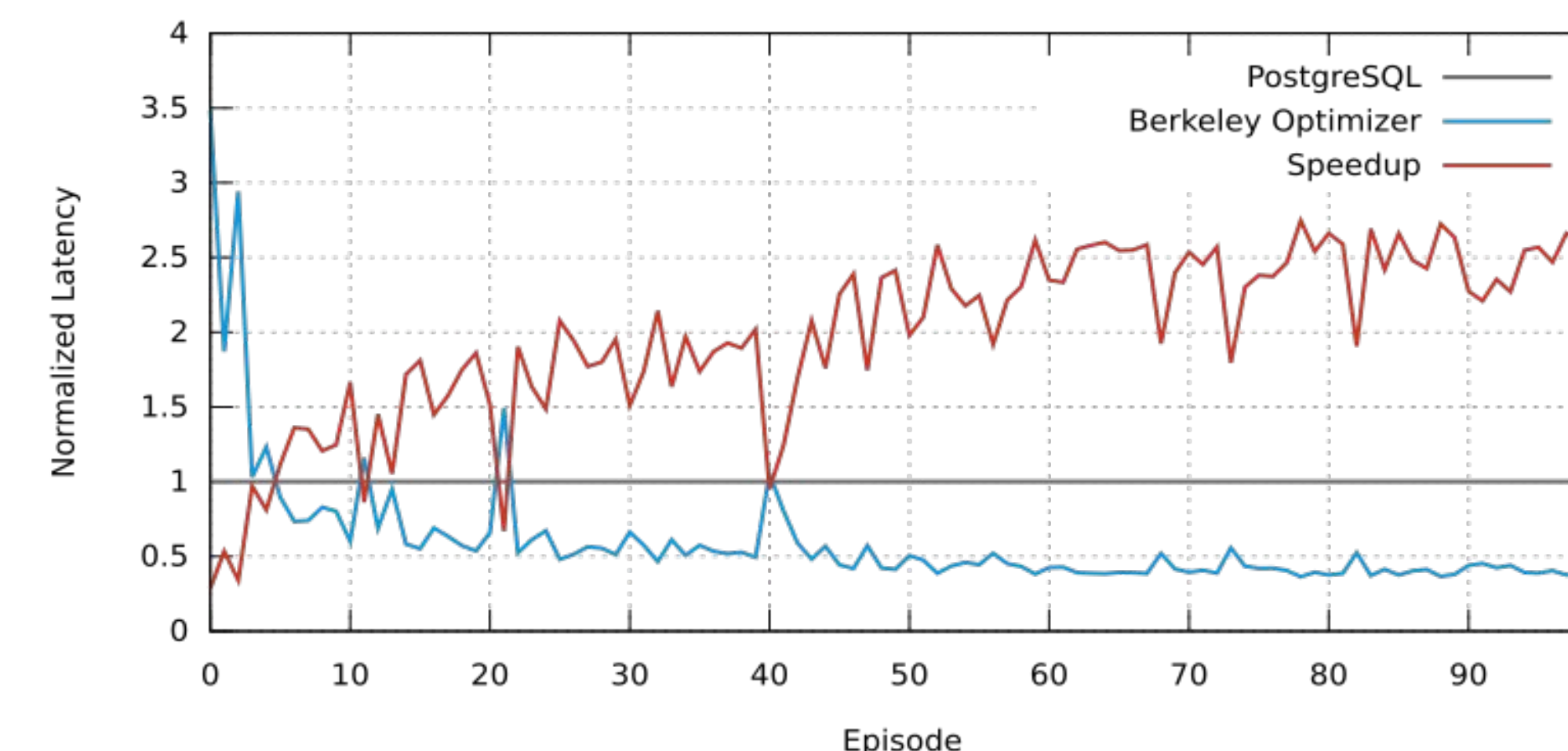
All experiments use the JOB (113 queries) benchmark.



Transformer with expert bootstrapping



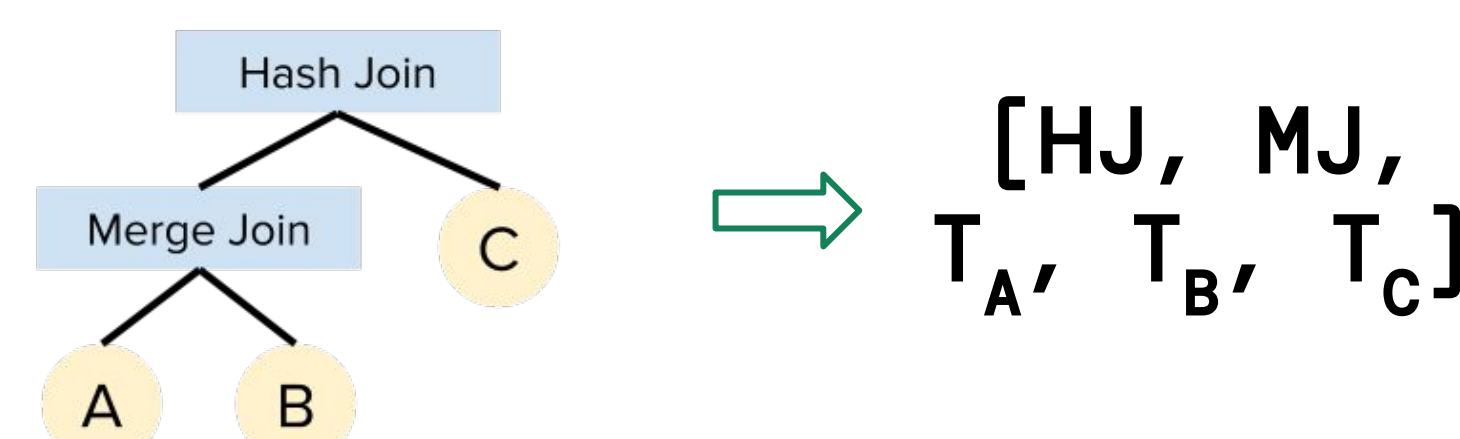
Tree convolution with expert bootstrapping



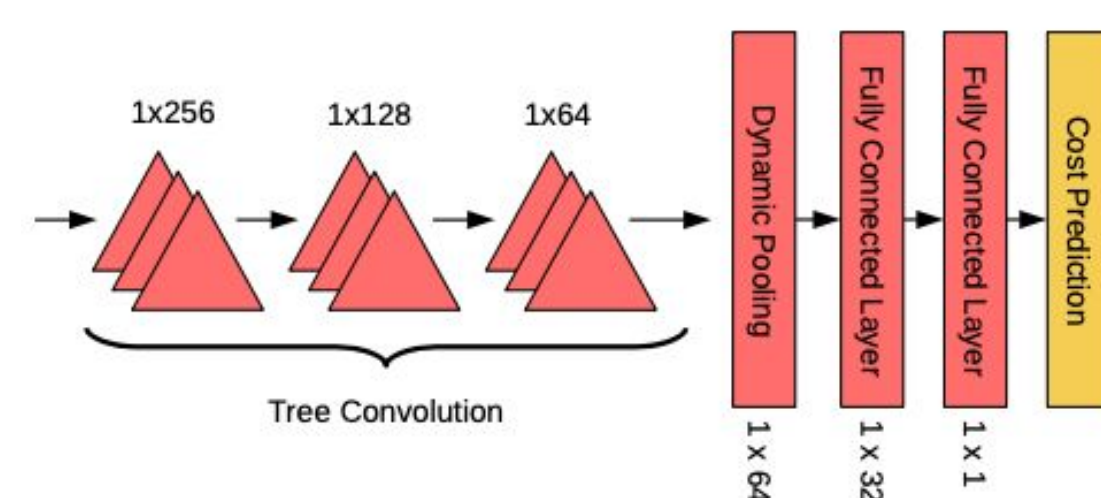
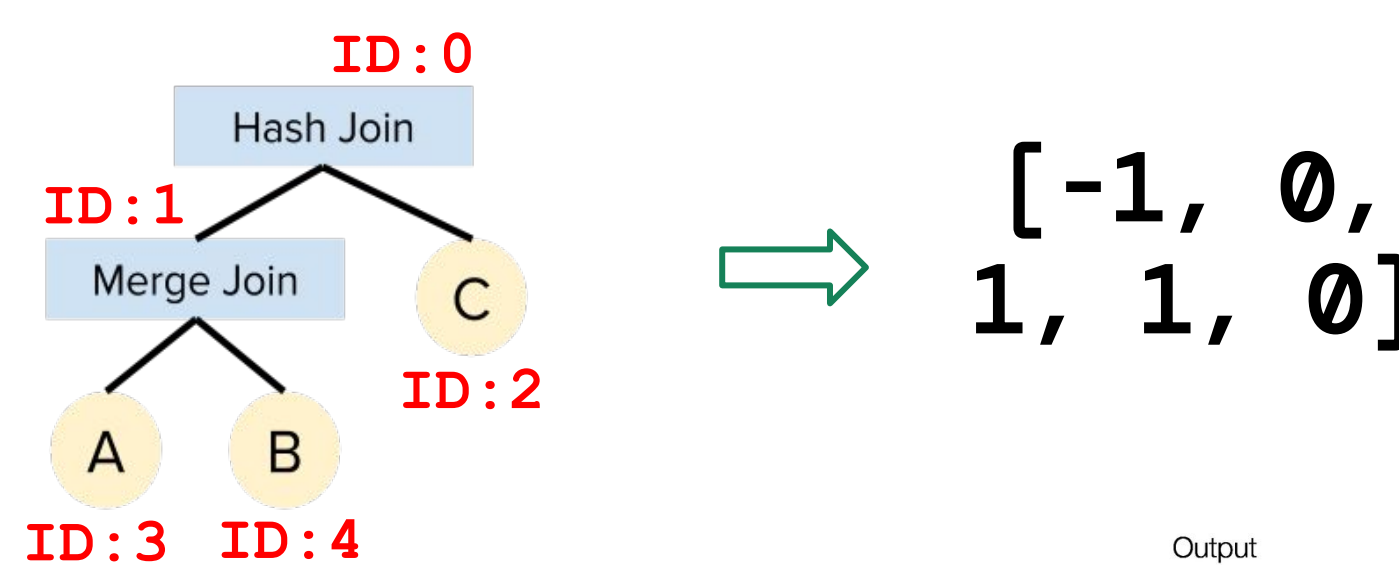
Transformer without expert bootstrapping

Encoding Plans as Sequences

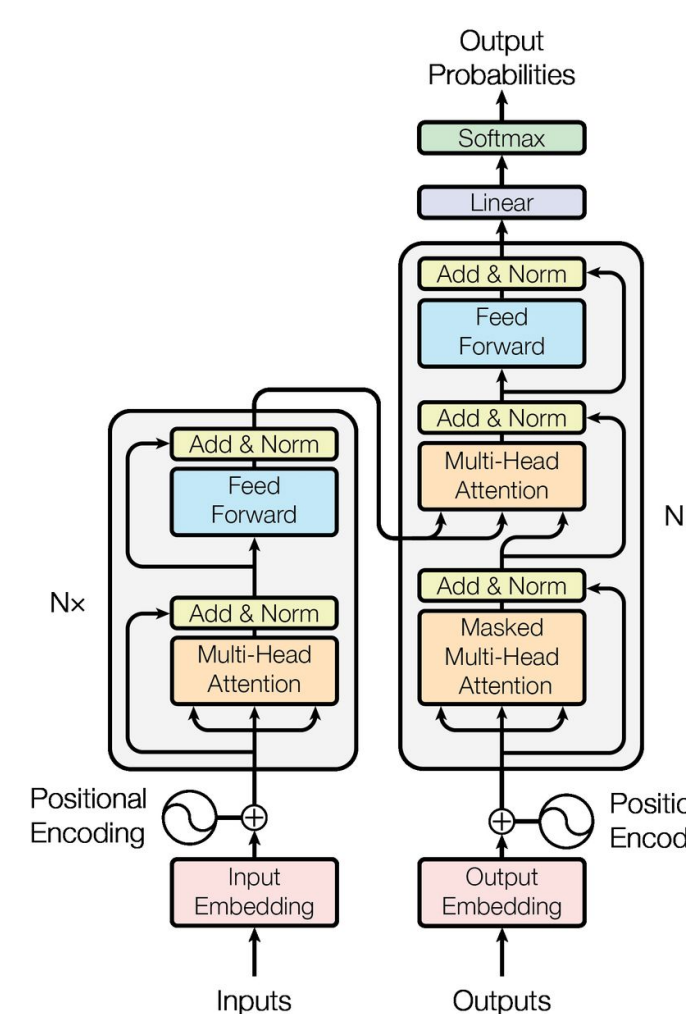
Pre-order Seq. Encoding



Parent Positional Embeddings (parent's ID)



Plan encodings are processed by either a transformer¹ or tree convolution² cost model.



[1] Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in Neural Information Processing Systems, pages 6000–6010.
[2] L. Mou, G. Li, L. Zhang, T. Wang, and Z. Jin. Convolutional neural networks over tree structures for programming language processing. In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence (AAAI'16), 2016.