An Index Advisor Using Deep Reinforcement Learning

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Index Selection Problem (ISP)

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- Choosing the right indexes to build is one of the central issues in database tuning.
- Problem Definition:
  - Select a set of indexes (index configuration) to be built to maximize the performance of the given workload with some constraints.
  - Constraints: storage usage, index number, and so on.

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- Index interaction: an interaction exists between an index a and an index b if the benefit of a is affected by the existence of b and vice-versa.

SELECT * FROM t WHERE a < 10 OR b < 10;

(1) An index on a ✗

(2) An index on b ✗

(3) An index on a and an index on b ✓

Prior Work

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Category	Work	Cost	Index type	IIA	Alog	Cons
Non-Learning method	AutoAdmin [VLD'97]	Estimated cost	S/M	✗	Greedy	index number
	ILP [ICDE'07]	Estimated cost	S/M	✗	ILP	storage
	ISRM [ICDE 19]	Estimated cost	S/M	✓	Greedy	storage
Learning-based method	AI Meet AI [SIGMOD'19]	Learning-model Estimated cost	S/M	Not sure	Greedy	index number
	Welborn et al [arxiv'19]	Not mention	S/M	✓	DQN	no
	DRL-Index [ICDEW'20]	Estimated cost	S	✓	DQN	Not mention

IIA means index interaction. **Cons** means constraints. **Alog** means search algorithm.
S means single column index. **M** means multi-column index.
Welborn's work only focuses on single table.
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Our Goal:

(1) Handle complex queries on multiple tables
(2) Recommend multi-column indexes
(3) Capture the index interaction

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Workload Sample → Rules → Index Candidates →

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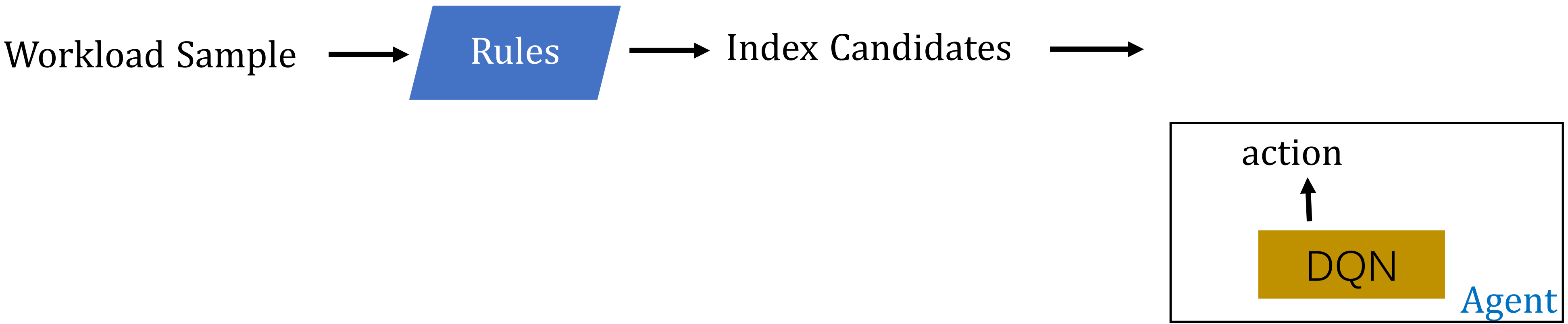

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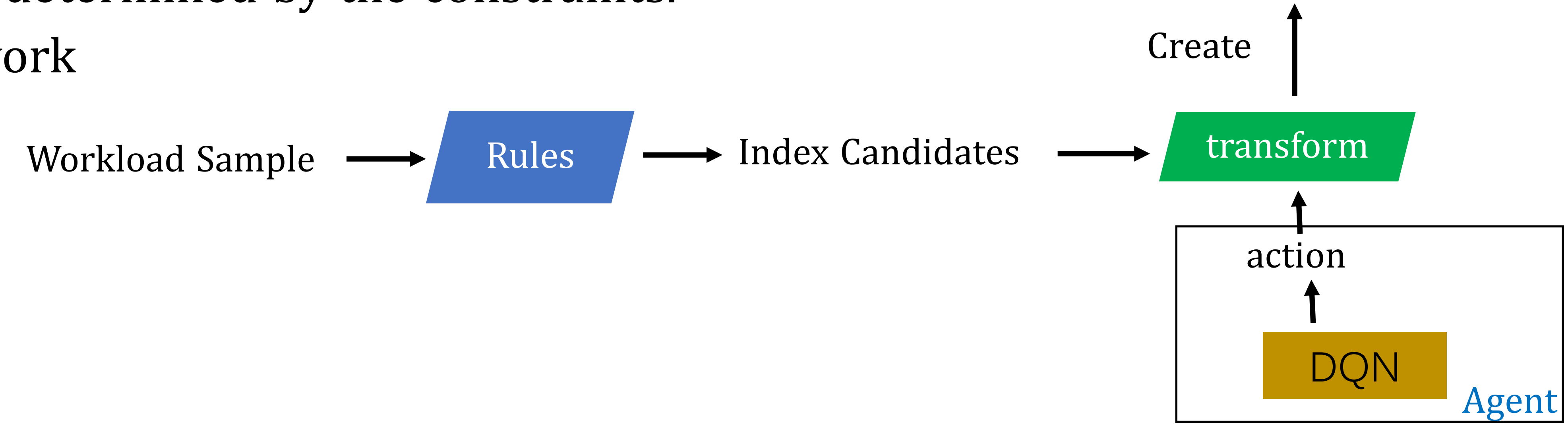

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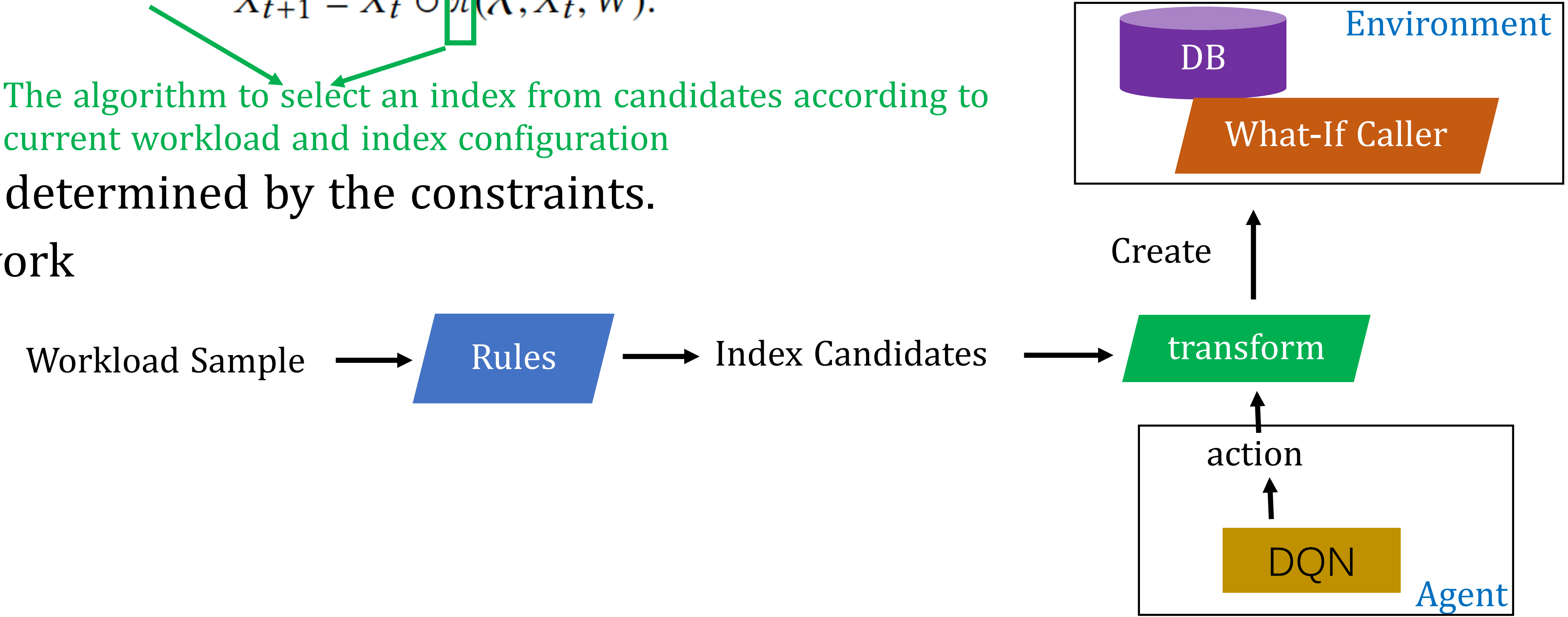

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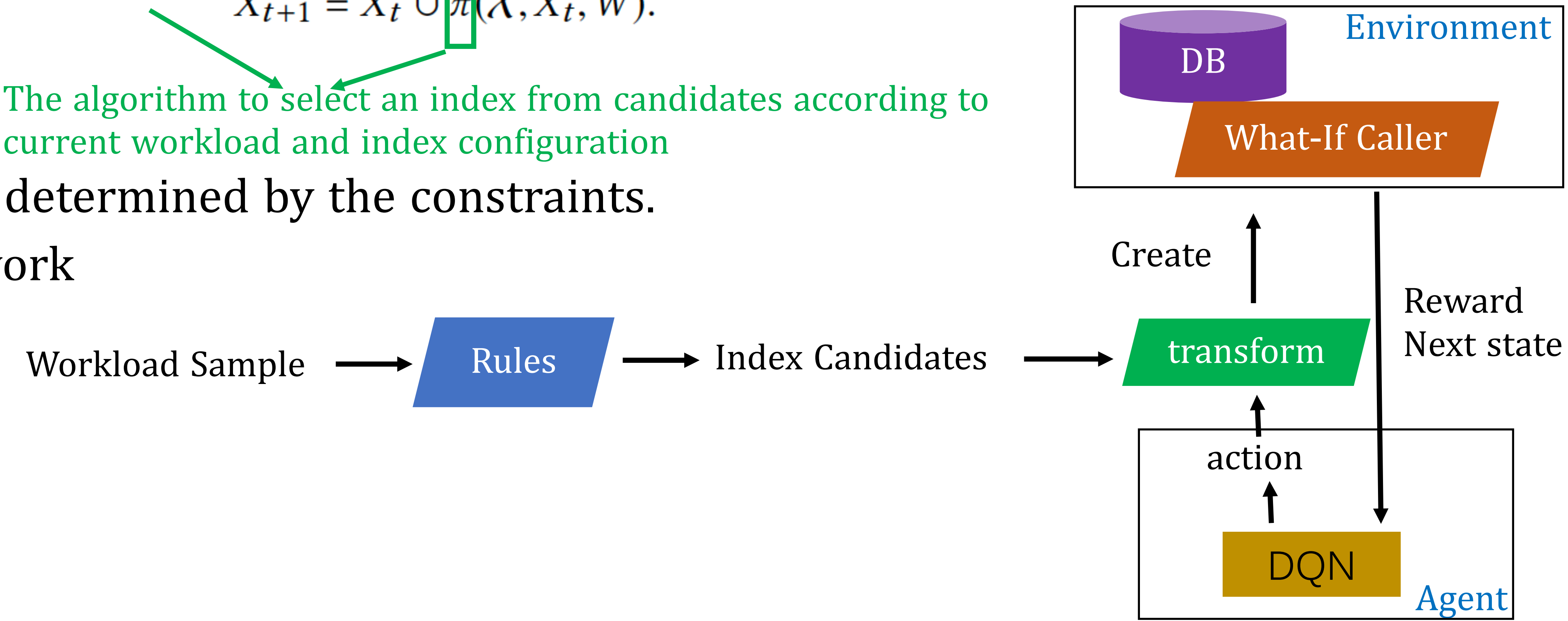

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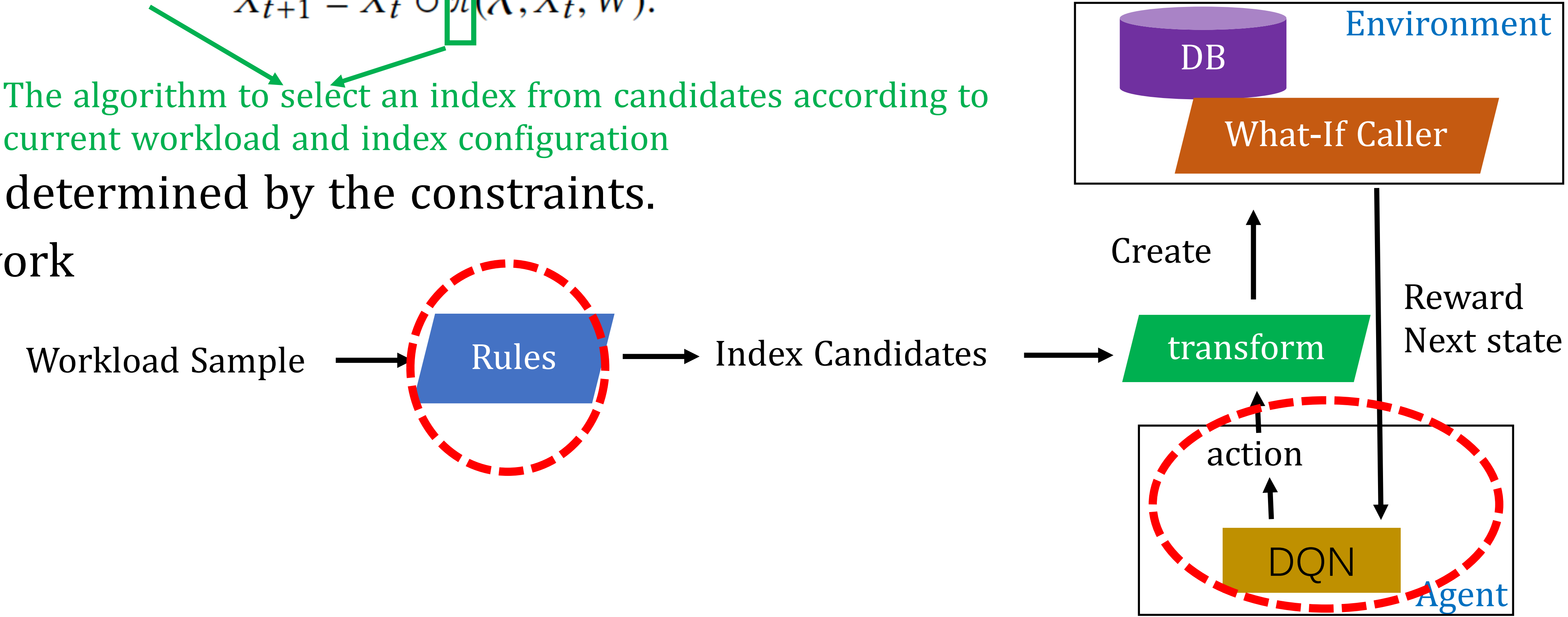

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Rule 4 & 5

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- Why we choose DQN model?
  - The action space is discrete, which is the same with Q-Learning and DQN
  - Q-Learning is only effective for small state space. However the state space in ISP is quite large.
  - DDPG is the algorithm for learning continuous actions.

Experiments

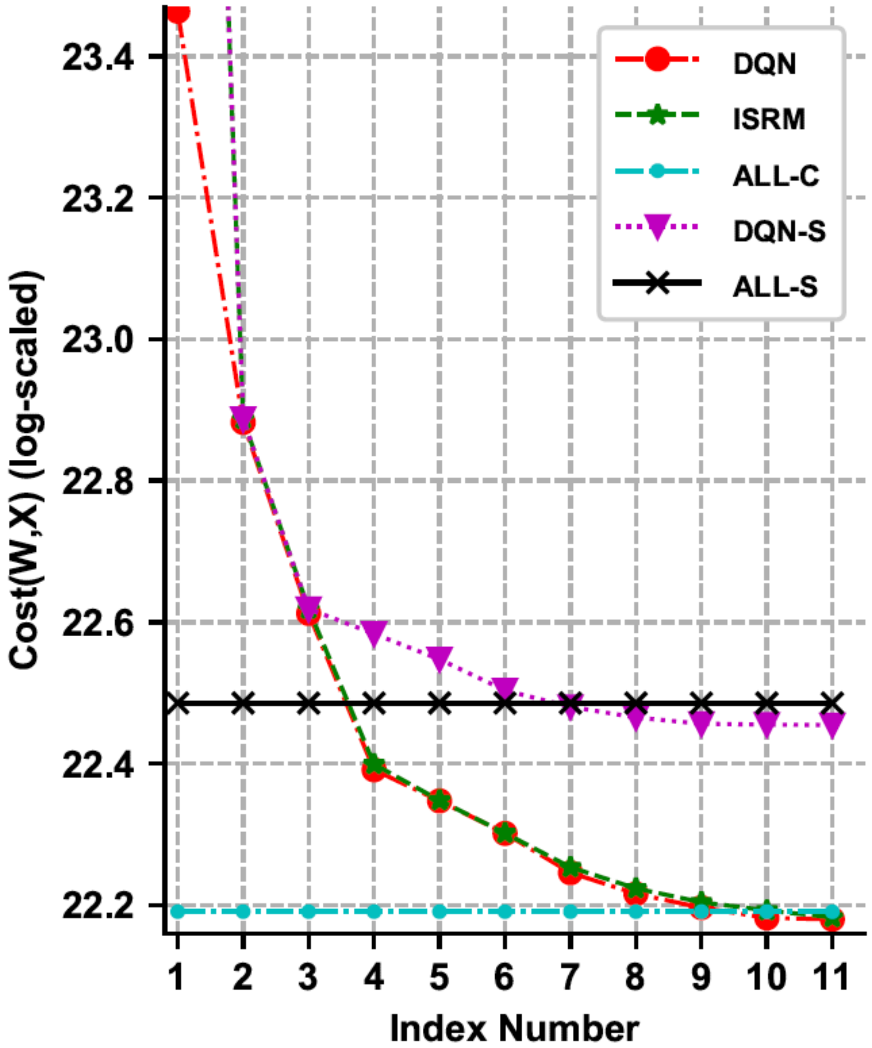
Question:

How well our method is compared with the current state-of-art method?

- Dataset: TPC-H with SF = 1
- Workload:
  - W^o (generated by the TPC-H query generator with 14 templates)
  - W^m (50 templates, queries on LINEITEM, multiple indexes)
- Evaluation Metric:
  - Estimated cost from optimizer
- Compared Methods:
  - ISRM [ICDE'19]

Experiments

- Index Selection on W^o for all tables



(1) W^o cannot get the best performance if only recommending single-attribute indexes by comparing ALL-S and ALL-C.

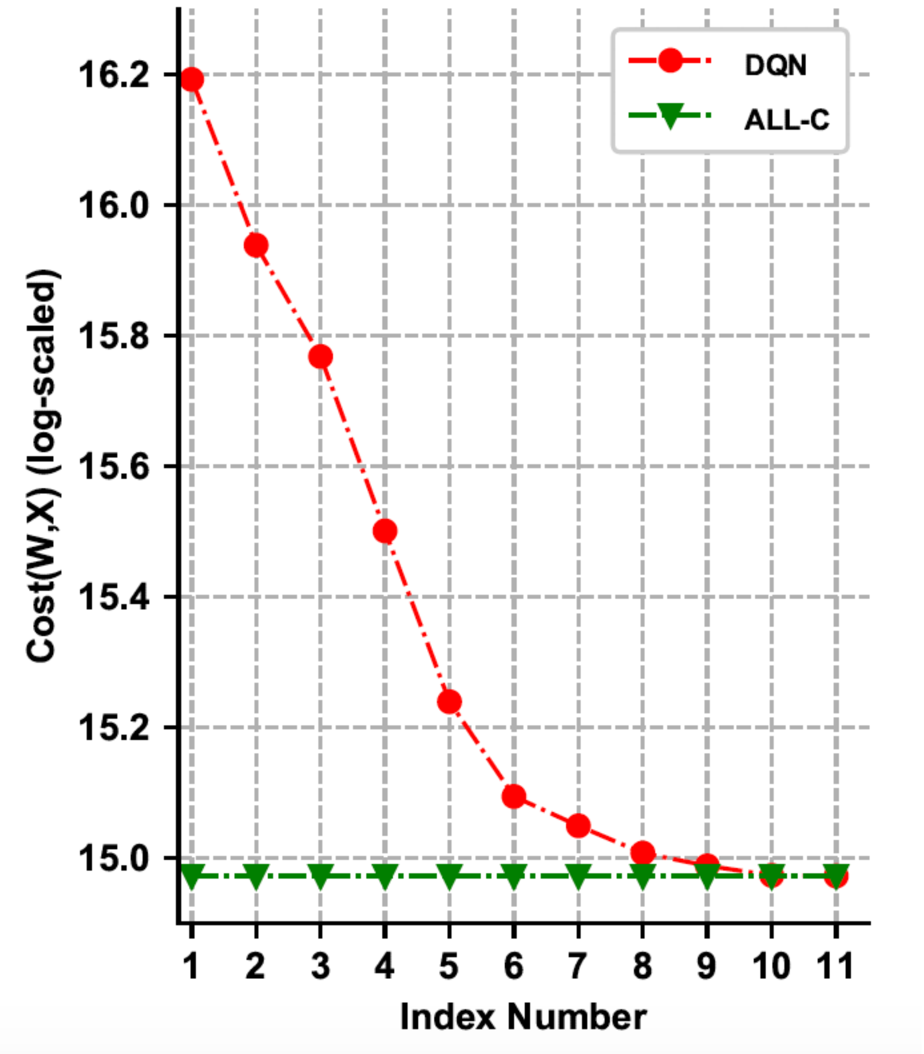
(2) When index number equals 1, the cost of W^o under DQN is much lower than DQN-S and ISMR.

(3) DQN-S and DQN get the optimal performance when index number is 7 and 10 separately. Even the costs of W^o under DQN-S and DQN can be lower than the optimal values.

(4) DQN is competitive to ISMR.

Experiments

- Index Selection on W^m



ISRM is sensitive to the order of attributes added in the algorithm.

Thank You
Q&A