Accelerating Joins with Filters

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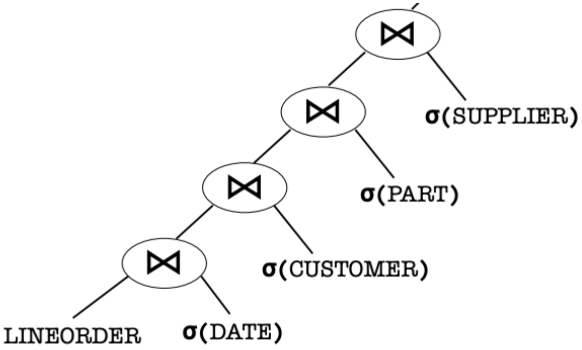
Star Schema



- If the query optimizer chooses a poor join order, intermediate join results may be unnecessarily large.
- Solution: try to filter out extraneous tuples before performing joins

Lookahead Information Passing (LIP)

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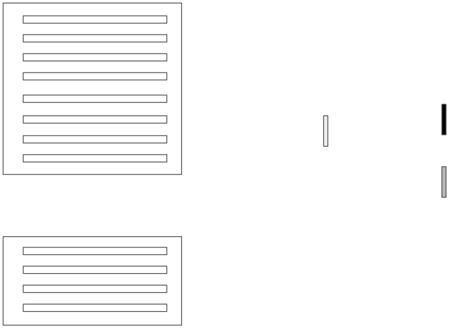

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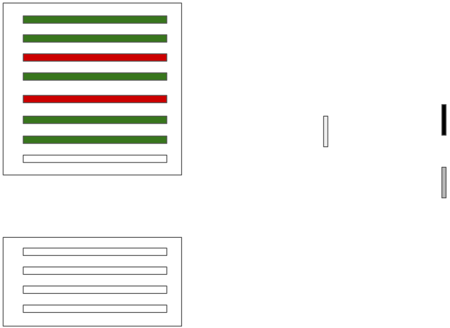

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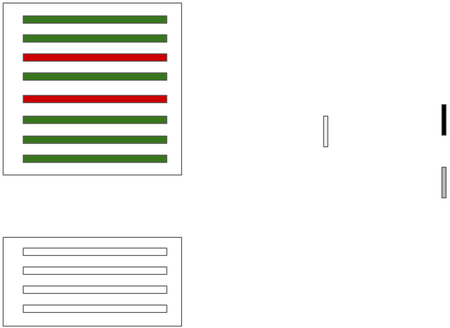

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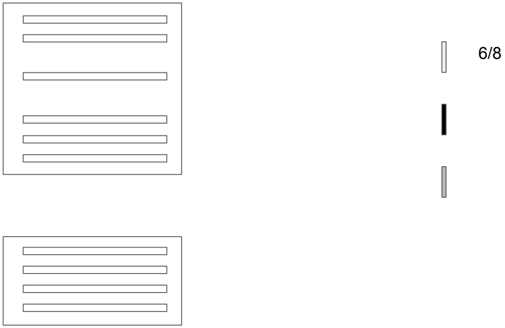

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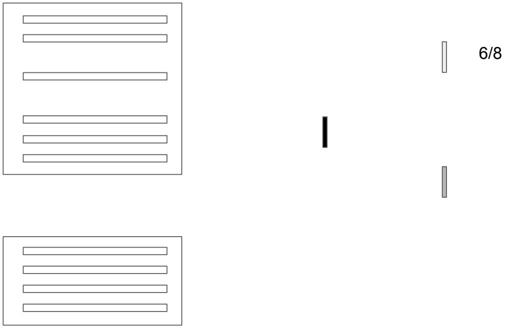

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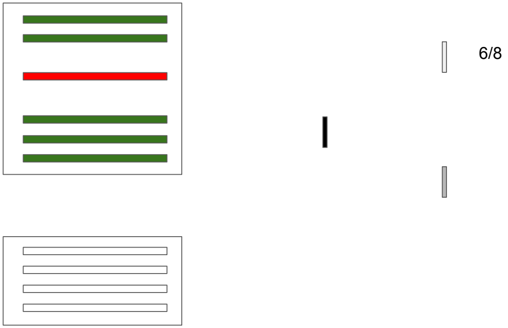

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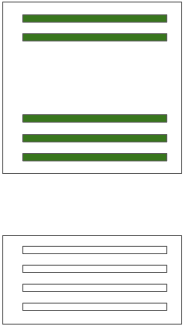

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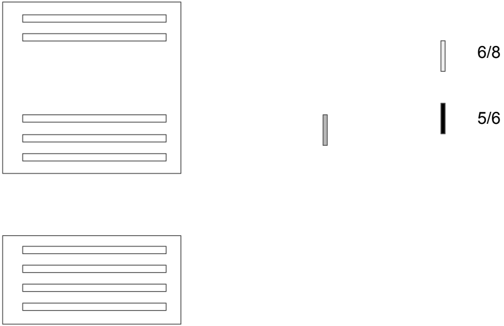

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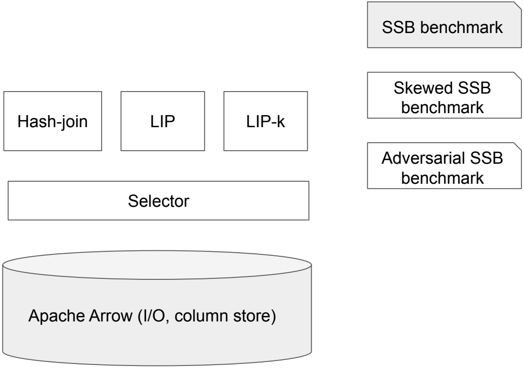
- LIP uses statistics from all previous batches to compute σ
  - Slow response to local changes in key distributions
- **LIP-k**: Only use the previous k batches to compute σ

Implementation and benchmarking



An Example Experiment

- Select where `Credit Score` ≥ 700

`Credit Score`	
720	
750	50 batches
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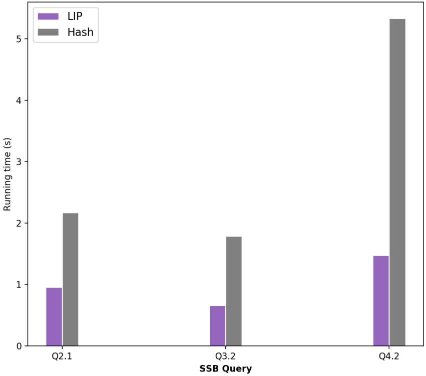

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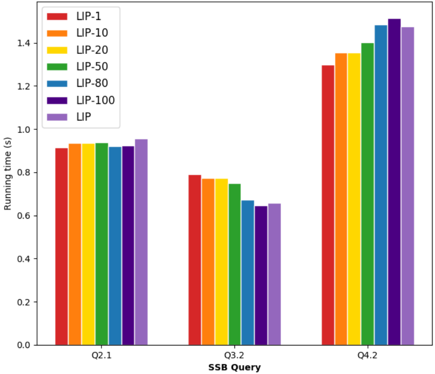

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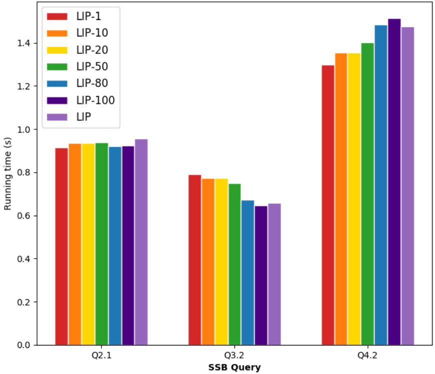

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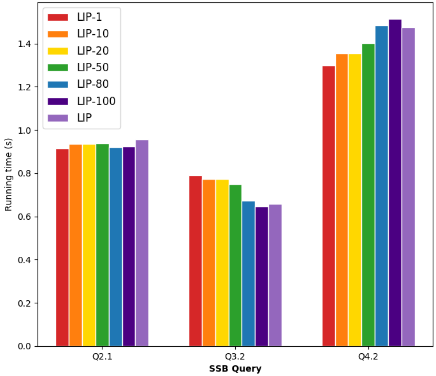

- LIP-k performs better than LIP on some queries...
- ...but LIP performs better on others

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Theorem

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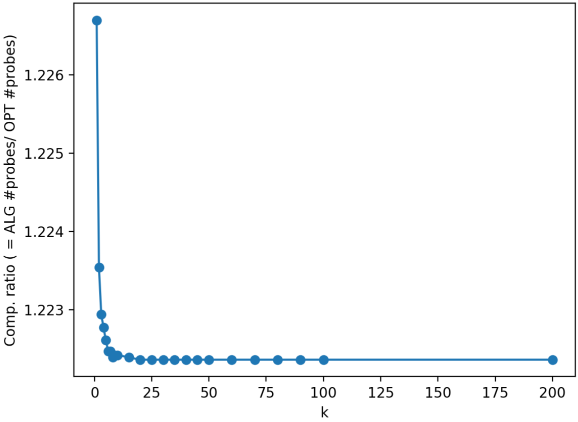
- Randomness?

Conclusion

- Implemented LIP and its variant LIP-k
- Relative performance of LIP and LIP-k depends on the query
- Can we use randomness to achieve a better robustness guarantee?

Thank you!

Competitive Ratio vs. k on Uniform Data



Competitive Ratio vs. k on Adversarial Data

- Adversarial data set constructed such that LIP-k has worst case performance for odd k
- Run on query with $N = 2$ joins