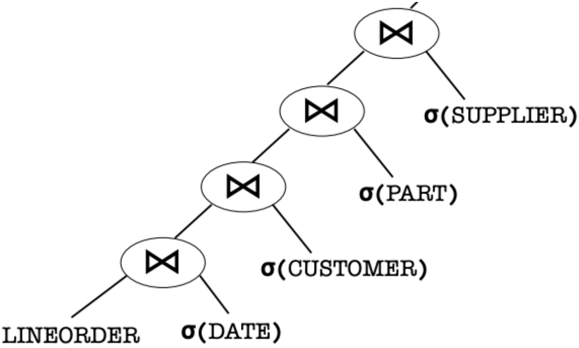
Accelerating Joins with Filters

Nicholas Corrado Xiating Ouyang

University of Wisconsin-Madison

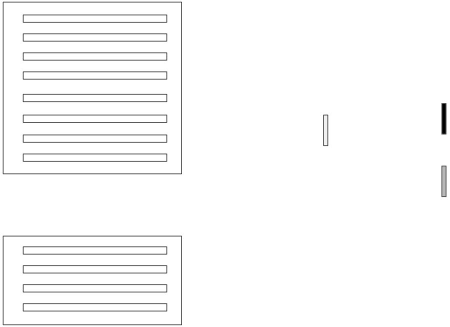
Star Schema



- 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)

Lookahead Information Passing (LIP)



Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

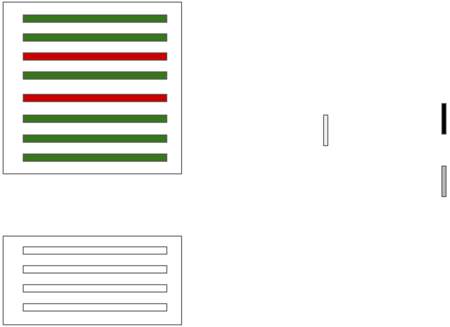
Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

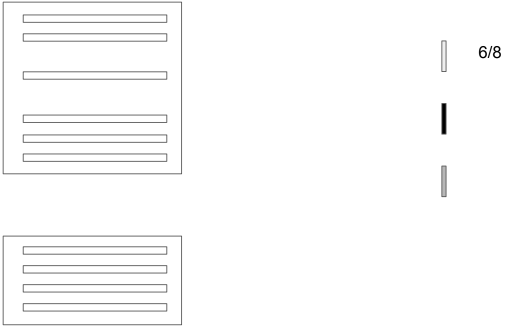


Lookahead Information Passing (LIP)

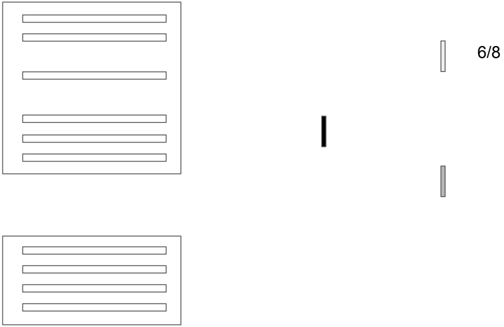
Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)



Lookahead Information Passing (LIP)



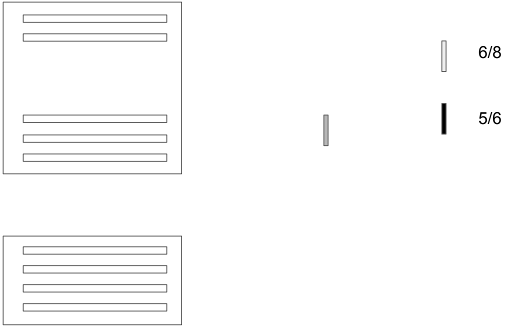
Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)



Lookahead Information Passing (LIP)

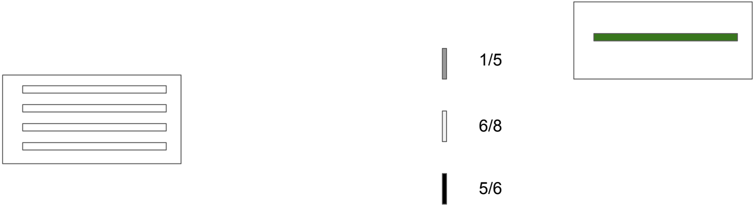
Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

Lookahead Information Passing (LIP)

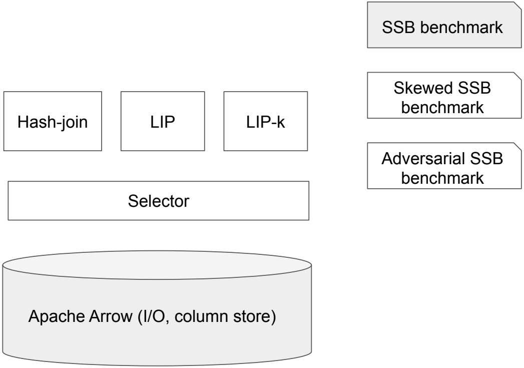
Lookahead Information Passing (LIP)



LIP-k

- LIP uses statistics from all previous batches to compute σ
  - Slow response to local changes in key distributions in fact table
  - e.g. (11/28/2019, Turkey)
- **LIP-k**: Only use the previous k batches to compute σ

Implementation and benchmarking



An Example Experiment

- Select where `Credit Score` $\geq$ 700

ID	
1	50 batches
2	
3	
...	
4	50 batches
5	
6	
...	
7	50 batches
8	
9	
...	

An Example Experiment

- Select where `Credit Score` $\geq$ 700

ID

1
2
3
...

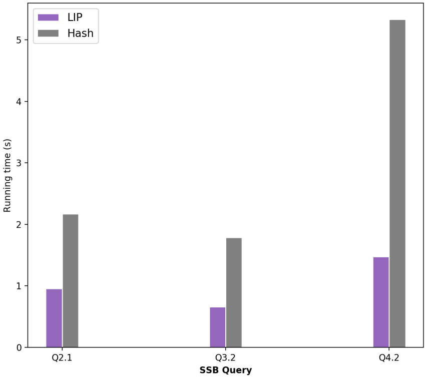
50 batches

4
5
6
...

50 batches

7
8
9
...

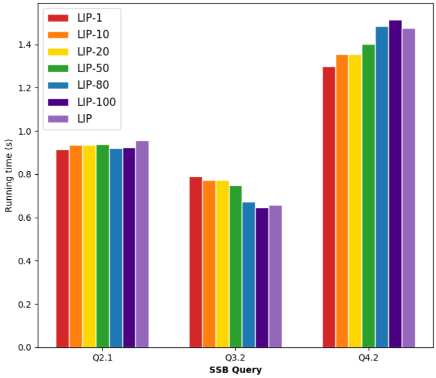
50 batches



An Example Experiment

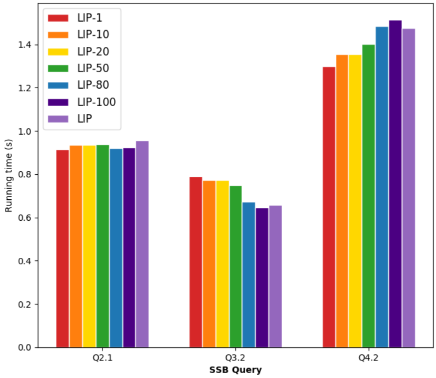
- Select where `Credit Score` $\geq$ 700

ID	
1 2 3 ...	50 batches
4 5 6 ...	50 batches
7 8 9 ...	50 batches



- Select where `Credit Score` ≥ 700

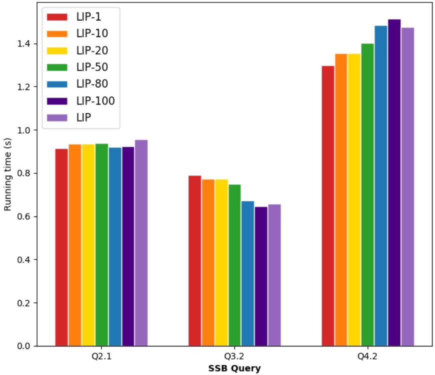
ID	
1	50 batches
2	
3	
...	
4	50 batches
5	
6	
...	
7	50 batches
8	
9	
...	



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

- Select where `Credit Score` ≥ 700

ID	
1 2 3 ...	50 batches
4 5 6 ...	50 batches
7 8 9 ...	50 batches



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

LIP is solving an online problem

- Given any tuple t, a mechanism $\mathcal{M}$ decides a sequence of applying the filters to *minimize* the number of probes.

LIP is solving an online problem

- Given any tuple t, a mechanism $\mathcal{M}$ decides a sequence of applying the filters to *minimize* the number of probes.
  - if t passes **all** filters: n probes necessary

LIP is solving an online problem

- Given any tuple t, a mechanism $\mathcal{M}$ decides a sequence of applying the filters to *minimize* the number of probes.
  - if t passes **all** filters: n probes necessary
  - if not, at least one filter rejects it: 1 probe best / n probes worst

LIP is solving an online problem

- Given any tuple t, a mechanism $\mathcal{M}$ decides a sequence of applying the filters to *minimize* the number of probes.
  - if t passes **all** filters: n probes necessary
  - if not, at least one filter rejects it: 1 probe best / n probes worst

$$\frac{\#\text{probes by } \mathcal{M} \text{ on } I}{\#\text{probes by OPT on } I} \leq n.$$

LIP is solving an online problem

- Given any tuple t, a mechanism $\mathcal{M}$ decides a sequence of applying the filters to *minimize* the number of probes.
  - if t passes **all** filters: n probes necessary
  - if not, at least one filter rejects it: 1 probe best / n probes worst

$$\max_I \frac{\#\text{probes by } \mathcal{M} \text{ on } I}{\#\text{probes by OPT on } I} \leq n.$$

LIP is solving an online problem

- Given any tuple t, a mechanism $\mathcal{M}$ decides a sequence of applying the filters to *minimize* the number of probes.
  - if t passes **all** filters: n probes necessary
  - if not, at least one filter rejects it: 1 probe best / n probes worst

$$\texttt{Competitive ratio of } \mathcal{M} = \max_{I} \frac{\#\text{probes by } \mathcal{M} \text{ on } I}{\#\text{probes by OPT on } I} \leq n.$$

LIP is solving an online problem

- Given any tuple t, a mechanism $\mathcal{M}$ decides a sequence of applying the filters to *minimize* the number of probes.
    - if t passes **all** filters: n probes necessary
    - if not, at least one filter rejects it: 1 probe best / n probes worst

$$\texttt{Competitive ratio of } \mathcal{M} = \max_{I} \frac{\#\text{probes by } \mathcal{M} \text{ on } I}{\#\text{probes by OPT on } I} \leq n.$$

Theorem

There is no **deterministic** *mechanism $\mathcal{M}$ for* LIP *achieving a competitive ratio less than N, where N is the number of filters used in* LIP.

LIP is solving an online problem

- Given any tuple t, a mechanism $\mathcal{M}$ decides a sequence of applying the filters to *minimize* the number of probes.
  - if t passes **all** filters: n probes necessary
  - if not, at least one filter rejects it: 1 probe best / n probes worst

$$\texttt{Competitive ratio of } \mathcal{M} = \max_{I} \frac{\#\text{probes by } \mathcal{M} \text{ on } I}{\#\text{probes by OPT on } I} \leq n.$$

Theorem

There is no **deterministic** *mechanism $\mathcal{M}$ for* LIP *achieving a competitive ratio less than N, where N is the number of filters used in* LIP.

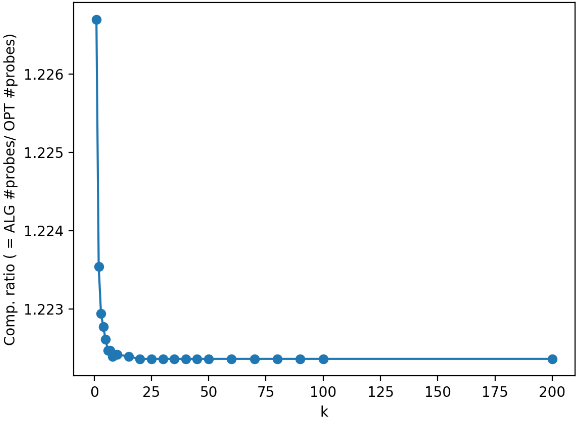
- Randomness?

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