Dalton: Learned Partitioning for Distributed Data Streams

Eleni Zapridou, Ioannis Mytilinis, Anastasia Ailamaki firstname.lastname@epfl.ch

1. Streaming challenges

Streaming engine

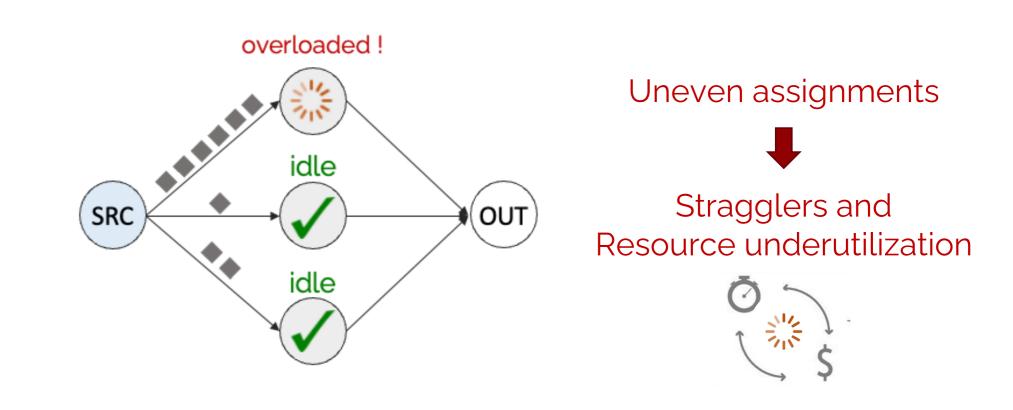
High input rate

Highly volatile workloads Continuous queries > Must adapt to the workload seamlessly

Performance constraints:

- Low latency
- Exact answers

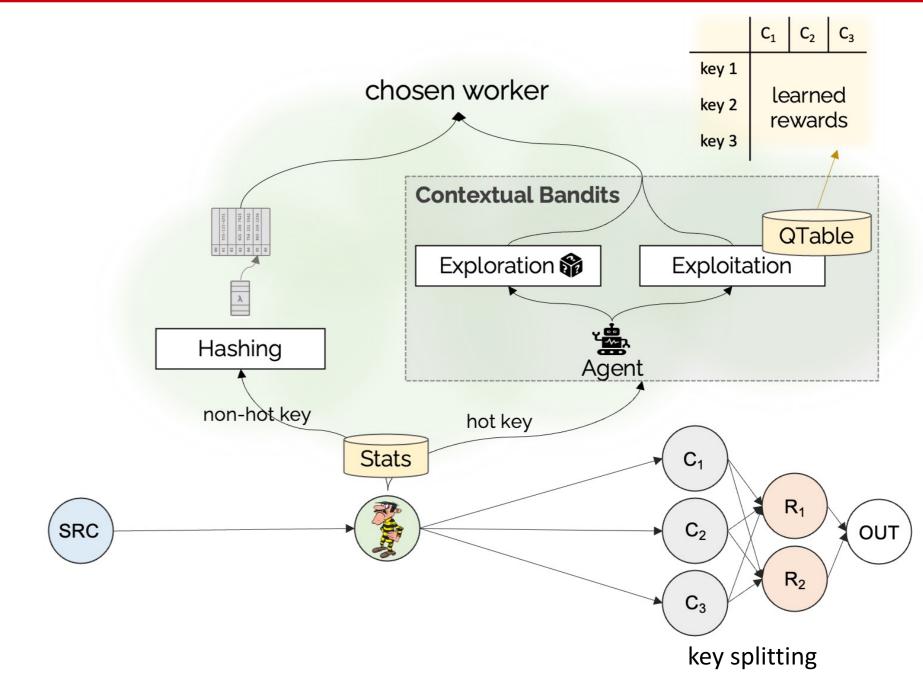
2. More resources \neq Better performance



3. Partitioning: How it is currently done

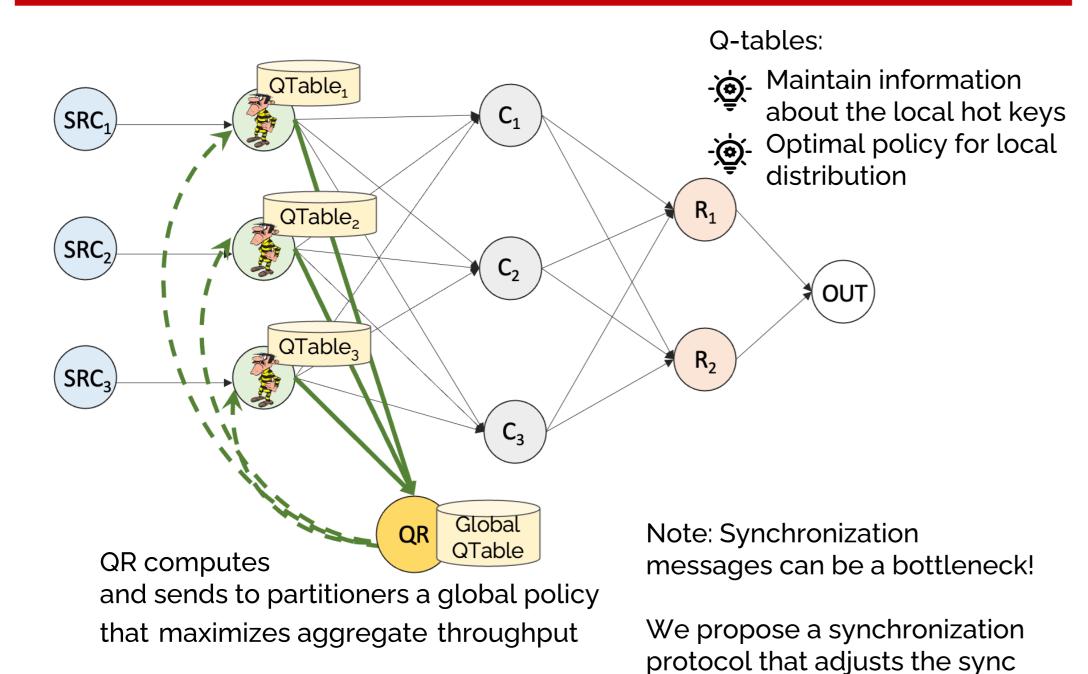
SELECT * FROM Stream S FLTR AGG **WHERE** S.v > 10 **GROUP BY S.k** Input **WINDOW 60 SLIDE 1** tuple parallel partitioning ▲ Intermediate window result for k aggregation Final result for k Hash partitioning Skewed workloads lead to stragglers ☀(out) Changing the hash function comes at the cost of state migration Key splitting Allows for balancing the load of partial aggregation SRC Final aggregation can become the bottleneck : split key final aggregation

4. Dalton adapts partitioning at runtime

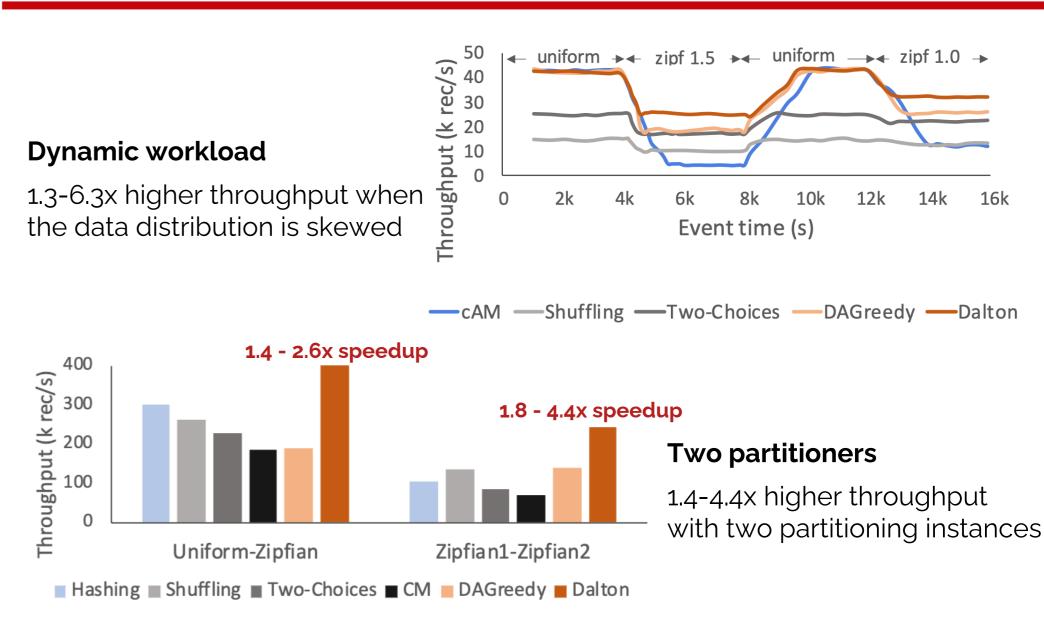


- Rewards computed by a cost model that balances partial and final aggregation
- Continuously learn rewards
- Exploitation: leverage acquired experience
- Exploration: is more splitting beneficial?

5. Dalton scales to many partitioners



6. Dalton maximizes throughput



Dalton is the only algorithm that adapts to the data distribution and scales to multiple instances

7. Conclusion

Dalton

learns partitioning policies at runtime with minimal overhead

frequency at runtime.

- quickly adapts to the distribution and is able to scale not only the processing workers but also the partitioners
- outperforms the state-of-the-art by a factor of 1.3-6.3x

8. More streaming challenges

- Unbounded data can lead to an unbounded state
- Multi-query optimization is crucial since queries run forever
- The query plan must be adapted upon addition of a new query

