When Two Choices Are not Enough: Balancing at Scale in Distributed Stream Processing

Anis Nasir Accepted at ICDE 2016, available at arXiv

Stream Processing



Stream Processing Engines

- Streaming Application
 - Online Machine Learning
 - Real Time Query Processing
 - Continuous Computation
- Streaming Frameworks

– Storm, S4, Flink Streaming, Spark Streaming

Stream Processing Model

 Streaming Applications are represented by Directed Acyclic Graphs (DAGs)





Stream Grouping

- Key or Fields Grouping (Hash Based)
 - Single worker per key
 - Stateful operators
- Shuffle Grouping (Round Robin)
 - All workers per key
 - Stateless Operators
- Partial Key Grouping
 - Two workers per key
 - MapReduce-like Operators

Key Grouping



- Scalable 🗮
- Low Memory
- Load Imbalance X

Shuffle Grouping



Aggregation O(W) X



- Low Memory
- Load Imbalance X

Partial Key Grouping





Problem Formulation

- Input is a unbounded sequence of messages from a key distribution
- Each message is assigned to a **worker** for processing (i.e., filter, aggregate, join)
- Load balance properties
 - Memory Load Balance
 - Network Load Balance
 - Processing Load Balance
- Metric: Load Imbalance

 $I(t) = \max_{i} (L_i(t)) - \arg_{i} (L_i(t)), \text{ for } i \in \mathcal{W}$



How to find optimal threshold?

- Any key that exceeds the capacity of two workers require more than two workers p_i ≥ 2/(n)
- We need to consider the collision of the keys while deciding the number of workers
- PKG guarantees nearly perfect load balance for p₁ ≤ 1/(5n)

How to find optimal threshold?



How many keys are in the Head?

Plots for the number of keys in Head for two different thresholds



How many workers for the Head?

• **D-Choices:** adapts to the frequencies of the keys in the Head

• W-Choices: allows all the workers for the keys in the head

• **Round-Robin:** employs shuffle grouping for the keys in the Head

How many workers for the Head?

• How to assign a key to set of d workers?

- Greedy-d: uses d different hash functions
 - generate set of d candidate workers
 - assign the key to least loaded of those workers
- In case of W-Choices, all the workers are the candidate for a key

How to find the optimal d?

 We can write our problem as an optimization problem

$$\begin{array}{ll} \text{minimize} & f(d;\mathcal{D},\theta) = d \times |\mathcal{H}_{\mathcal{D},\theta}| \\ \text{subject to} & & & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ \end{array} f(d;\mathcal{D},\theta) = d \times |\mathcal{H}_{\mathcal{D},\theta}| \end{array}$$

How to find optimal d?

• We can rewrite the constraint

$$\sum_{i \le h} p_i + \left(\frac{b}{n}\right)^d \sum_{h < i \le |H|} p_i + \left(\frac{b}{n}\right)^2 \sum_{i > |H|} p_i \le \left(\frac{b}{n}\right) + \varepsilon$$

• For instance for the first key with p1

$$p_1 + \left(\frac{b}{n}\right)^d \sum_{1 < i \le |H|} p_i + \left(\frac{b}{n}\right)^2 \sum_{i > |H|} p_i \le \left(\frac{b}{n}\right) + \varepsilon$$

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where

$$b = n - n \left(\frac{n-1}{n}\right)^{h \times d}$$

What are the values of d?



Memory Overhead

• Compared to PKG



Memory Overhead

• Compared to SG



Experimental Evaluation

• Datasets

Dataset	Symbol	Messages	Keys	$p_1(\%)$
Wikipedia Twitter Cashtags	WP TW CT	22M 1.2G 690k	2.9M 31M 2.9k	$9.32 \\ 2.67 \\ 3.29$
Zipf	ZF	10^{7}	$10^4, 10^5, 10^6$	$\propto rac{1}{\sum x^{-z}}$

Experimental Evaluation

• Algorithms

Symbol	Algorithm	Head vs. Tail
D-C W-C RR	D-Choices W-Choices Round-Robin	Specialized on head
PKG SG	Partial Key Grouping Shuffle Grouping	Treats all keys equally

How good are estimated d?

 Comparison of estimated d versus the minimal experimental value of d



Load Imbalance for Zipf



Load balance for real workloads

 Comparison of D-C, WC with PKG in terms of load balance



Load Imbalance over time

 Load imbalance over time for the real-world datasets



Throughput on real DSPE

 Throughput on a cluster deployment on Apache Storm for KG, PKG, SG, D-C, and W-C on the ZF dataset



Latency on a real DSPE

 Latency (on a cluster deployment on Apache Storm for KG, PKG, SG, D-C, and W-C



Conclusion

- We propose two algorithms to achieve load balance at scale for DSPEs
- Use heavy hitters to separate the head of the distribution and process on larger set of workers
- Improvement translate into 150% gain in throughput and 60% gain in latency over PKG

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