

Improving *Tug-of-War* sketch using Control-Variates method

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Streaming Datasets

- ❑ Many data sources that generates **large volume** of data are best **modeled** as **data stream**
e.g. : streams of network packets, click stream data, traffic data etc.
- ❑ Impractical to **store** and **process** the **entire data**
- ❑ By taking **one pass** over data, quickly build a **small summary** (a.k.a. sketch)
- ❑ Perform computation on **sketch** to get **approximate answer**



k -th moment and Inner product

- Universe = { a, b, c,, z } (size of universe is n)
- $\sigma_1 = a, b, a, d, c, b, b, d, e, \dots$ and $\mathbf{f} = (f_1, f_2, \dots, f_n)$ is corresponding frequency vector.
- $\sigma_2 = a, b, a, d, c, e, c, d, e, b \dots$ and $\mathbf{g} = (g_1, g_2, \dots, g_n)$ is corresponding frequency vector.
- k -th moment of σ_1 and σ_2 is

$$\mathbf{F}_k = \sum_{i \in [n]} f_i^k \quad \text{and} \quad \mathbf{G}_k = \sum_{i \in n} g_i^k \quad (1)$$

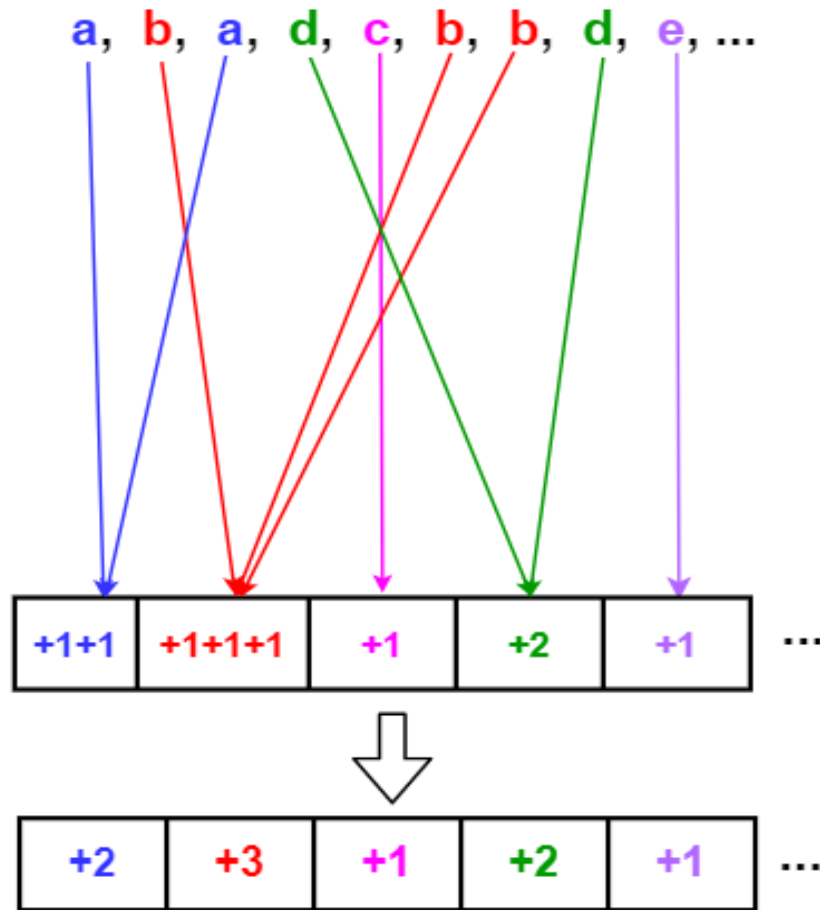
- Inner product of \mathbf{f} and \mathbf{g} is

$$\langle \mathbf{f}, \mathbf{g} \rangle = \sum_{i \in [n]} f_i \cdot g_i \quad (2)$$

- Our focus is to find
 - F_2 moment of the stream
 - Inner product



Naive Method to Compute F_2 moment



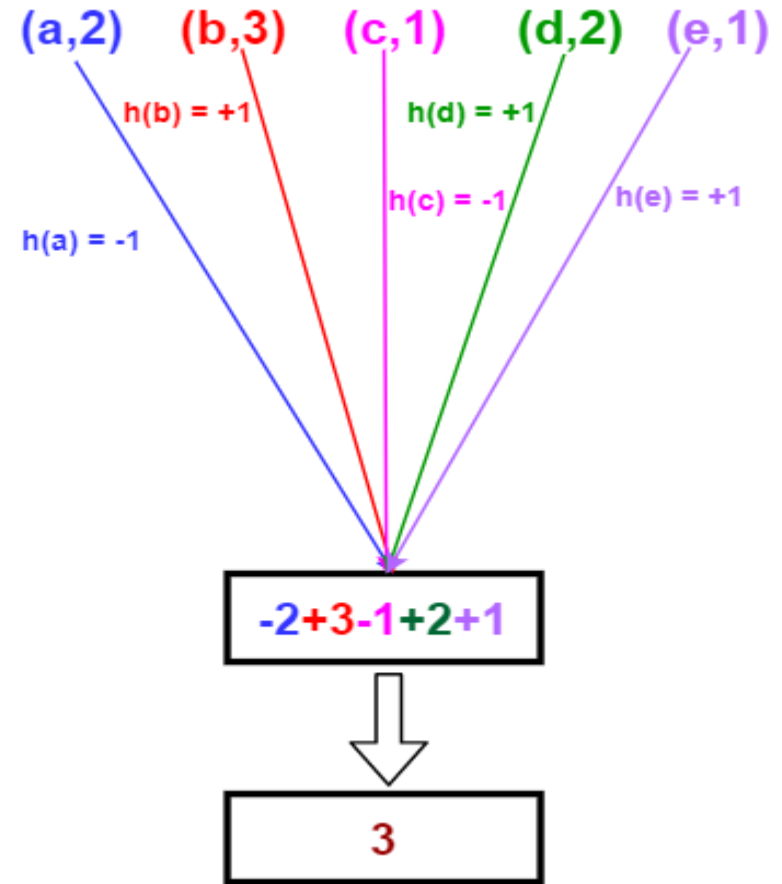
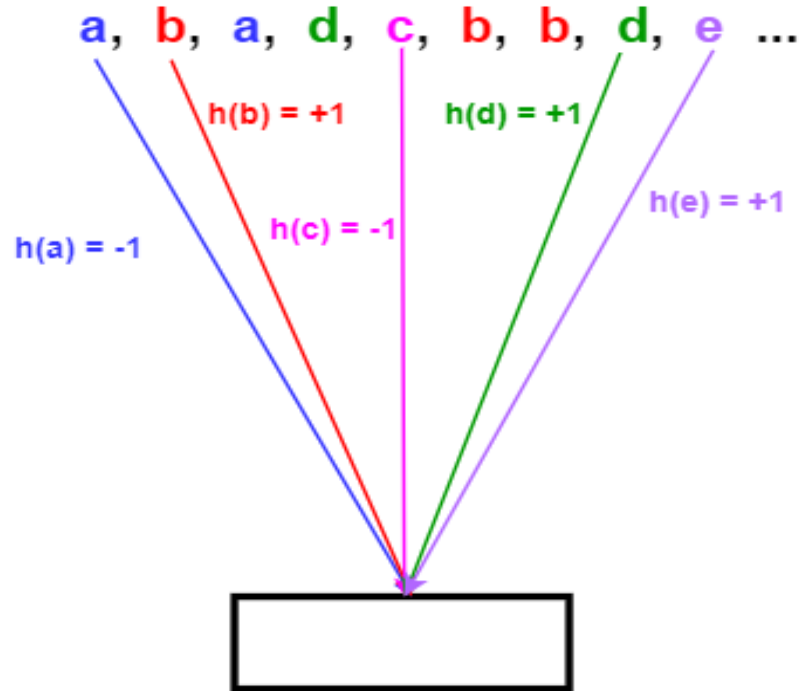
$$F_2 = 2^2 + 3^2 + 1^2 + 2^2 + 1^2 + \dots$$

- ❑ Data stream of alphabets of length m .
- ❑ Universe: $= [n] = \{a, b, \dots, z\}$
- ❑ f_i is frequency of i^{th} item, $i \in [n]$.
- ❑ $f = (f_1, f_2, \dots, f_n)$ is a frequency vector.
- ❑ Space requirement: $O(n \log m)$.

Impractical when n and m are very large.



F_2 estimation of a data-stream using *Tug-of-War* sketch



Estimated $F_2 = 3^2 = 9$

Actual $F_2 = 2^2 + 3^2 + 1^2 + 2^2 + 1^2 = 19$

Space required : $O(\log m + \log n)$



F_2 estimation of a data-stream using *Tug-of-War* sketch

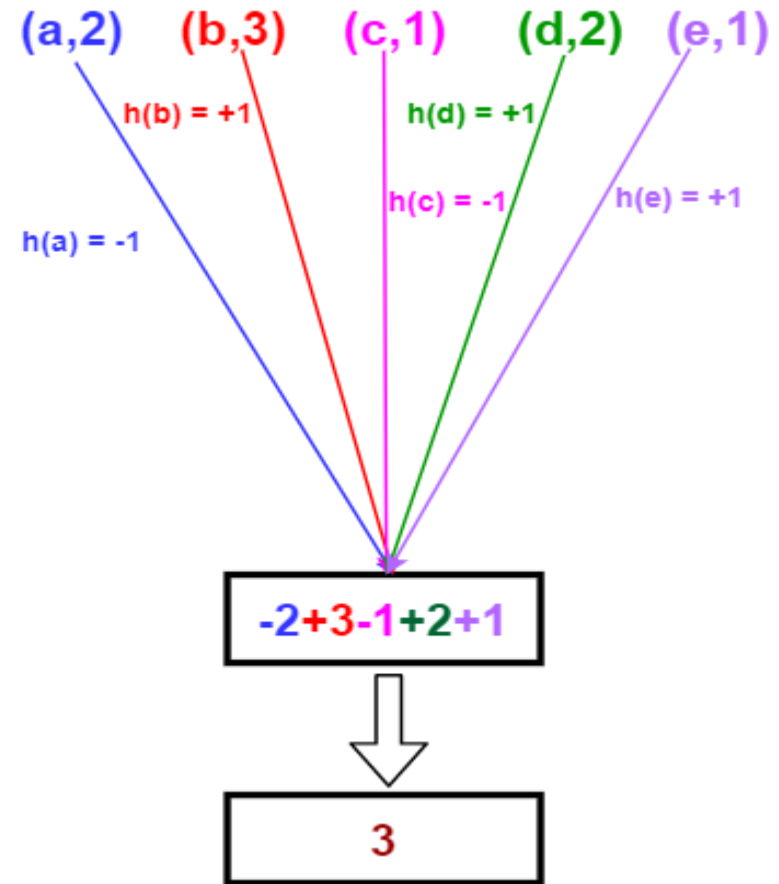
- $h[n] \rightarrow \{+1, -1\}$
- f_i frequency of i^{th} item
- Frequency Vector: $\mathbf{f} = (f_1, f_2, \dots, f_n)$

Estimating F_2 :

$$\tilde{X} = \sum_{i \in [n]} f_i h(i)$$

$$X = \tilde{X}^2$$

X is the estimate of F_2



$$\text{Estimated } F_2 = 3^2 = 9$$

$$\text{Actual } F_2 = 2^2 + 3^2 + 1^2 + 2^2 + 1^2 = 19$$



F_2 estimation of a data-stream using *Tug-of-War* sketch

$$\tilde{X} = \sum_{i \in [n]} f_i h(i)$$

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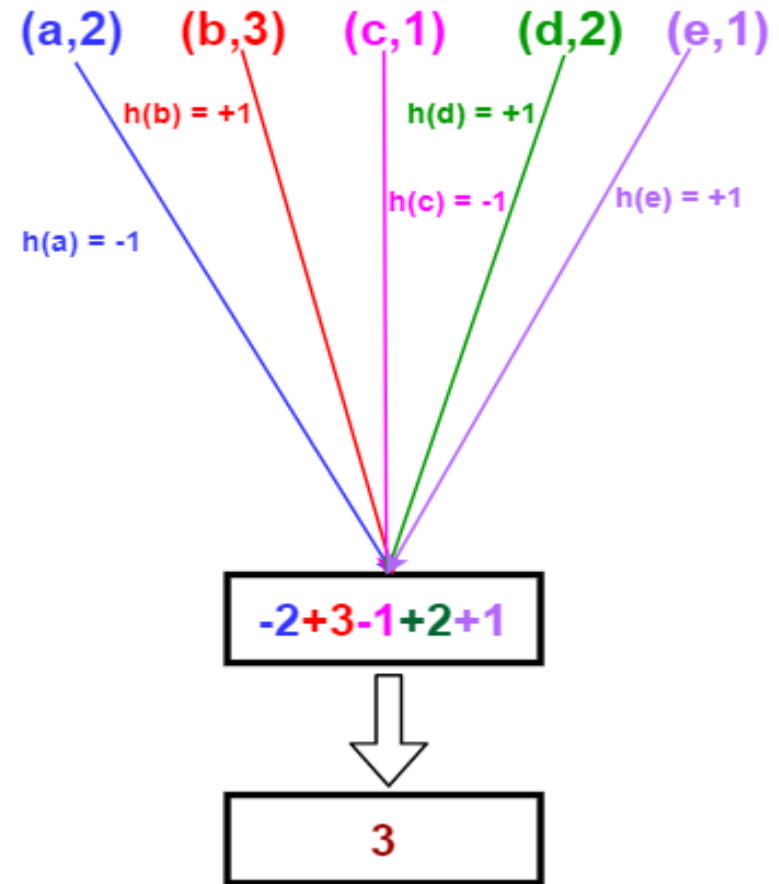
□ Statistics of X

$$E[X] = \|f\|_2^2 = F_2 \quad (3)$$

and

$$\text{Var}[X] = 2(F_2^2 - F_4) \quad (4)$$

Variance is high for large values of f_i



Estimated F_2 : $X = 3^2 = 9$

Actual $F_2 = 2^2 + 3^2 + 1^2 + 2^2 + 1^2 = 19$



Variance reduction via Control-Variate (CV)

- Let X be the r.v. of our estimate
- Find another r.v. Z s.t. $E[Z]$ is known
- Our new estimator: $X + c(Z - E[Z])$

$$E[X + c(Z - E[Z])] = E[X]. \quad (5)$$

$$\text{Var}[X - c(Z - E[Z])] = \text{Var}[X] + c^2 \text{Var}[Z] + 2 \text{Cov}[X, Z]. \quad (6)$$

Optimal value of c which minimize equ. (6), say \hat{c} is

$$\hat{c} = -\frac{\text{Cov}[X, Z]}{\text{Var}[Z]}. \quad (7)$$

Equation (6) and (7), gives

$$\text{Var}[X + c(Z - E[Z])] = \text{Var}[X] - \frac{\text{Cov}[X, Z]^2}{\text{Var}[Z]}. \quad (8)$$



Variance reduction via Control-Variate (CV)

Properties of Z :

- ❑ should be **easily computable**
- ❑ should have **low variance**
- ❑ should have **high covariance with X**
- ❑ $E[Z]$ should be **known**



Improving Tug-of-War using Control-Variate (CV) Method

Tug-of-war estimate: $X = \left(\sum_{i \in [n]} f_i h(i) \right)^2$

We choose CV r.v. $Z = \sum_{i \neq j, i, j \in [n]} h(i)h(j)$

$\Rightarrow E[Z] = 0$ and $Var[Z] = F_0(F_0 - 1)$,

$$Cov[X, Z] = F_1^2 - F_2$$

where $F_0 := n$ and $F_1 := \sum_{i \in [n]} f_i$.

$$\hat{c} = -\frac{Cov[X, Z]}{Var[Z]} = -\frac{F_1^2 - F_2}{F_0(F_0 - 1)} \quad (9)$$

$$\text{Variance Reduction} = \frac{Cov[X, Z]^2}{Var[Z]} = \frac{(F_1^2 - F_2)^2}{F_0(F_0 - 1)} \quad (10)$$



Improving Tug-of-War using Control-Variate (CV) Method

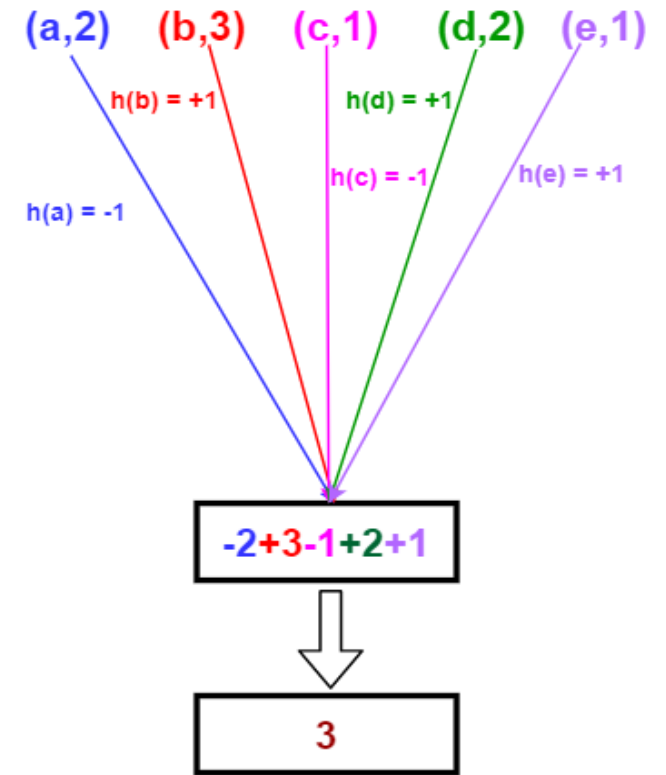
□ $X = 9$ (Tug-of-war estimate), $Z = -4$, and $E[Z] = 0$.

□ Recall $\hat{c} = -\frac{F_1^2 - F_2}{F_0(F_0 - 1)}$.

□ We compute F_1 by maintaining a counter (in space $O(\log m)$).

□ For F_2 , we use Tug-of-War estimate as a proxy.

Our CV estimate:
$$\begin{aligned} X + \hat{c}(Z - E[Z]) &= 9 - \frac{(81 - 9)}{5(5 - 1)}(-4 - 0) \\ &= 9 - 3.6 \times (-4) \\ &= \mathbf{23.4} \end{aligned}$$



Estimated F_2 : $X = 3^2 = 9$

Actual $F_2 = 2^2 + 3^2 + 1^2 + 2^2 + 1^2 = \mathbf{19}$



Empirical Evaluation

Datasets

❑ Synthetic Datasets

- stream of 100000 items
- frequency of each item is sampled randomly between 1 and 5000.

❑ KOS dataset

- consist of corpus of document, treat word as an item and number of occurrences in entire corpus as frequency
- consist of 6906 distinct word and their frequency

❑ Transaction datasets

- T10I4D100K: consist of 870 distinct items and 1010228 item in total
- T40I10D100K: consist of 942 distinct items and 3960507 items in total



Empirical Evaluation

Evaluation Metrics:

- ❑ Variance analysis via box-plot
- ❑ Mean absolute error
- ❑ Median of means estimation

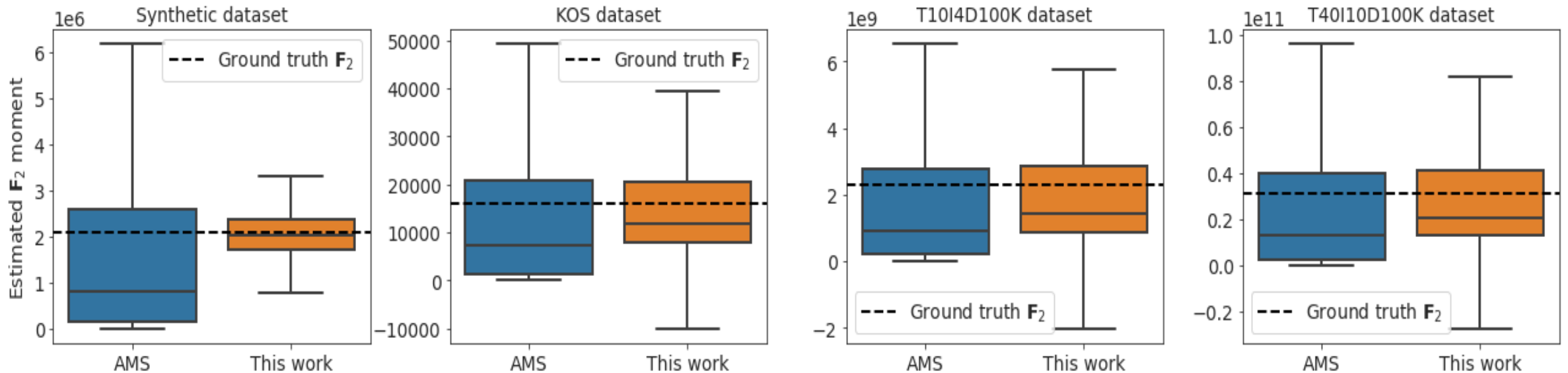


Figure 1



Empirical Evaluation

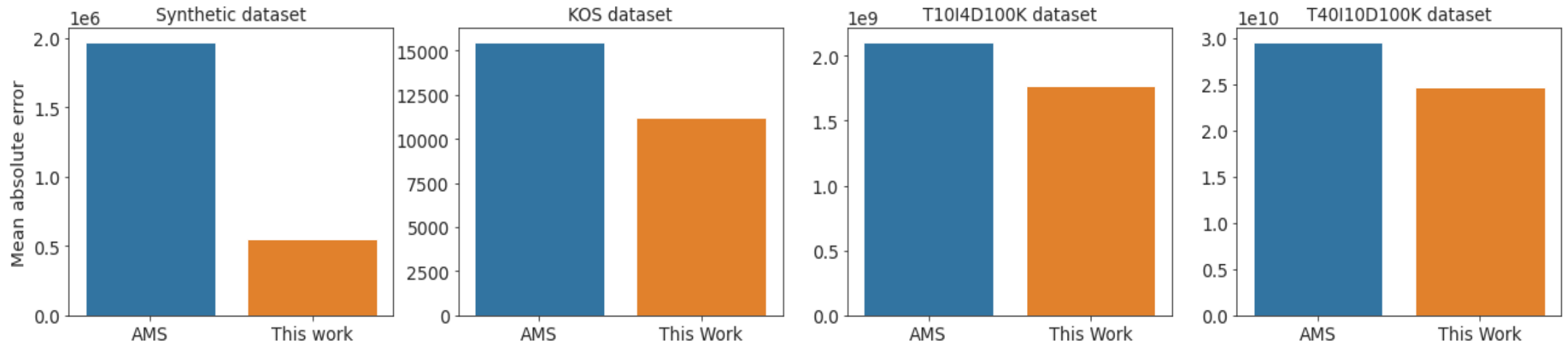


Figure 2

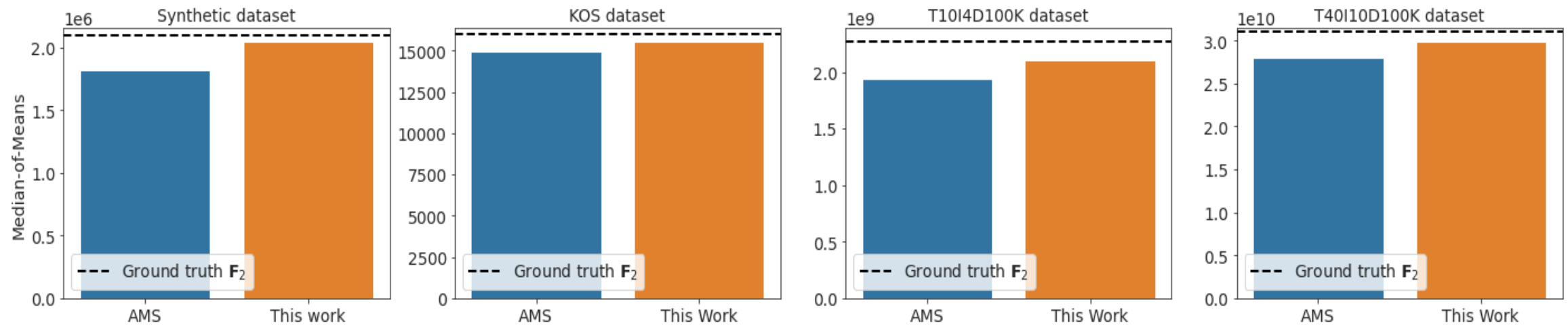


Figure 3



Improving Inner product estimate using CV method

- $\mathbf{f} = (f_1, f_2, \dots, f_n)$ is a frequency vector of stream σ_1 .
- $\mathbf{g} = (g_1, g_2, \dots, g_n)$ is a frequency vector of stream σ_2 .
- *Tug-of-War* sketch of streams σ_1 and σ_2 are

$$\tilde{\mathbf{f}} = \sum_{i \in [n]} f_i h(i) \quad \text{and} \quad \tilde{\mathbf{g}} = \sum_{i \in [n]} g_i h(i)$$

- Inner product estimate of \mathbf{f} and \mathbf{g} is

$$X^{(2)} = \tilde{\mathbf{f}} \cdot \tilde{\mathbf{g}}$$

- $E[X^{(2)}] = \langle \mathbf{f}, \mathbf{g} \rangle$ (11)

- $Var[X^{(2)}] = \sum_{i \neq j, i, j \in [n]} f_i^2 g_i^2 + \sum_{i \neq j, i, j \in [n]} f_i g_i f_j g_j$ (12)

Variance is high for large value f_i and g_i



Improving Inner product estimate using CV method

Tug-of-war estimate: $X^{(2)} = \tilde{f} \cdot \tilde{g} = (\sum_{i \in [n]} f_i h(i)) (\sum_{i \in [n]} g_i h(i))$

We choose CV r.v. $Z^{(2)} = \tilde{f}^2 + \tilde{g}^2$

$$\Rightarrow E[Z^{(2)}] = F_2 + G_2 \quad \text{and} \quad Var[Z^{(2)}] = 2(2\langle f, g \rangle + F_2^2 + G_2^2) \quad (13)$$

$$Cov[X^{(2)}, Z^{(2)}] = 2\langle f, g \rangle(F_2 + G_2) \quad (14)$$

$$\hat{c} = -\frac{Cov[X^{(2)}, Z^{(2)}]}{Var[Z^{(2)}]} = -\frac{\langle f, g \rangle(F_2 - G_2)}{(2\langle f, g \rangle + F_2^2 + G_2^2)} \quad (15)$$

$$\text{Variance reduction} = \frac{Cov[X^{(2)}, Z^{(2)}]^2}{Var[Z^{(2)}]} = \frac{2(\langle f, g \rangle(F_2 - G_2))^2}{(2\langle f, g \rangle + F_2^2 + G_2^2)} \quad (16)$$



Improving Inner product estimate using CV method

□ Our CV estimate of inner product : $X^{(2)} + \hat{c}(Z^{(2)} - E[Z^{(2)}])$

Recall:

$$Z^{(2)} = \tilde{f}^2 + \tilde{g}^2 \quad \text{and} \quad E[Z^{(2)}] = F_2 + G_2,$$

and

$$\hat{c} = -\frac{\langle f, g \rangle (F_2 - G_2)}{(2\langle f, g \rangle + F_2^2 + G_2^2)}$$

□ For $\langle f, g \rangle$, we use $X^{(2)}$ as a proxy.

□ For F_2 and G_2 , we use \tilde{f}^2 and \tilde{g}^2 obtained by Tug-of-War sketch as a proxy.



Empirical Evaluation

Datasets

- ❑ **Synthetic dataset:** We generate a pair of stream using same procedure mentioned for F_2^2 estimation
- ❑ **KOS dataset:** We split the corpus into two equal halves consisting of the same number of documents, and we consider each half as a separate data stream.
- ❑ **Transaction datasets:** we split the streams in two equal halves and consider each half as a separate data stream

Evaluation Metrics:

- ❑ Variance analysis via box-plot
- ❑ Mean absolute error
- ❑ Median of means estimation



Empirical Evaluation

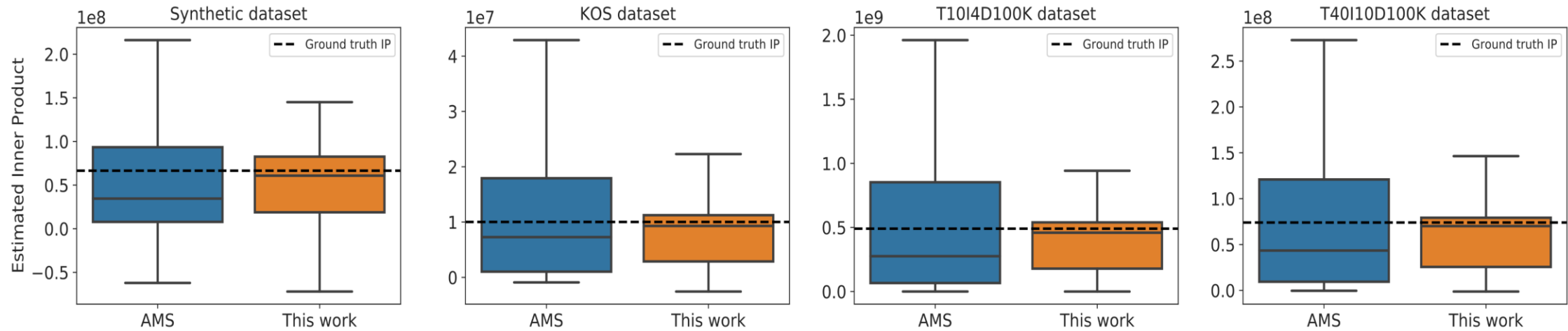


Figure 4

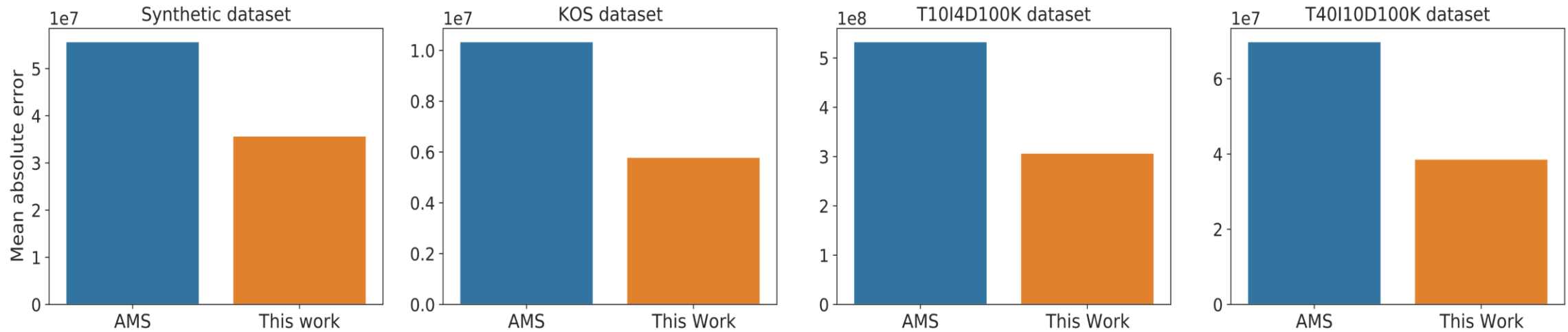


Figure 5



Empirical Evaluation

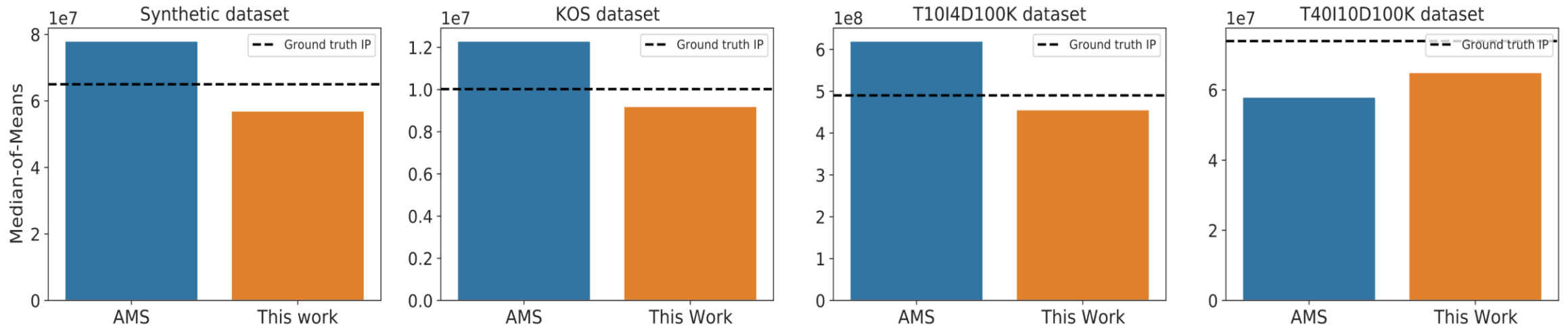


Figure 6



Conclusion and Open Questions

Summary

- ❑ Improving Tug-of-War algorithm for F_2 and Inner product estimation using Control-Variate Method.
- ❑ Less overhead and nice empirical performance.

Open Questions

- ❑ Better candidate for Control-variate random variable Z ?
- ❑ Possibility of applying in other streaming/randomized algorithms?



Thank You

Questions ?

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References

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- Lavenberg, S. S., & Welch, P. D. (1981). A perspective on the use of control variables to increase the efficiency of Monte Carlo simulations. *Management Science*, 27(3), 322-335.

