Flink Frequent Item Detection

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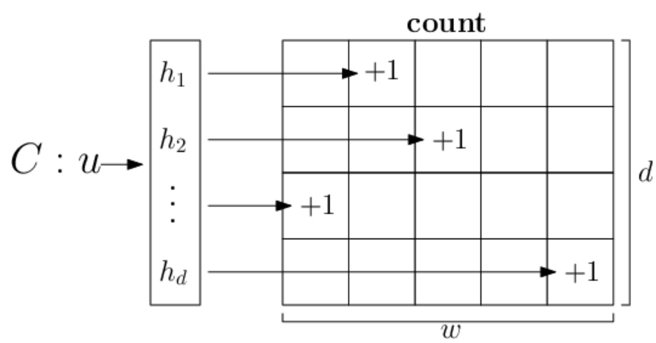
Motivation

Online storefronts such as Amazon conduct millions of transactions every day for a wide range of products. Analyzing trends in this data can require intensive computation. We implemented a space-efficient distributed system to determine which items and categories are trending. The system empowers businesses and customers alike to make informed decisions about products.

Design Description

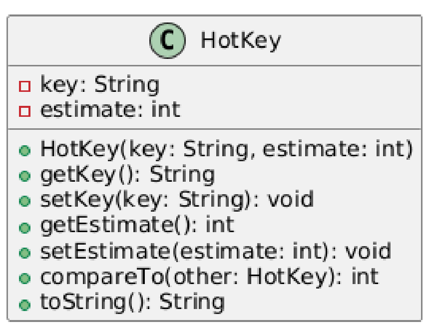
The Amazon Sales Dataset contains ~1,400 rows of item purchases from Amazon, including product names and categories. To construct an unbounded stream from this data, we created a rate-limited data source which generates random purchases from a distribution over item categories. This distribution can be tuned by specifying weights for each category in resources/weights.yaml. If the total weight of these specified categories is less than 100%, the remaining weight is uniformly distributed over unspecified categories. The dataset itself is stored as a CSV file, and the logic to parse it leverages OpenCSV and resides in stream/PurchaseGenerator.

To estimate frequent items in the stream, we implemented the count-min sketch (CMS) data structure in cms2D/Sketch. CMS uses sublinear space, which makes it perfect when handling large data streams. Each Sketch encapsulates a 2D array of estimates. Each row in the array is associated with a MurmurHash3.hash32x86 hash function. When an item arrives, its category is passed through each hash function, and the hashes are used to increment the counters of the corresponding rows. Notice counters never underestimate with this scheme, so the minimum counter is the best estimate for a given category's frequency.



To achieve a distributed CMS, incoming items are randomly distributed across NUM_CORES workers using a RandomKeySelector. Workers run the WindowCMS process, which creates and updates a local Sketch object. After a set time interval, the workers submit their local sketches to a global coordinator running the Merger process. Sketches are merged by simply adding corresponding entries.

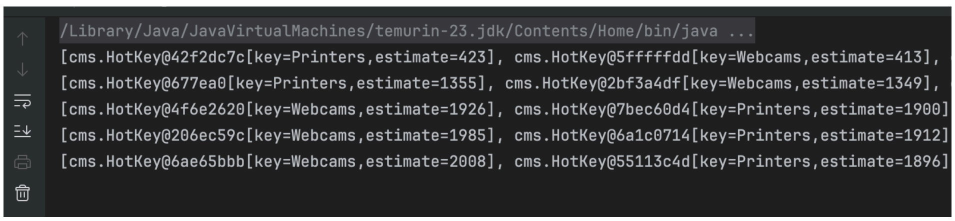
Assuming the number of categories can be arbitrarily large, it would be costly to extract estimates for every category from a merged CMS. Instead, our solution has each worker maintain a size-limited TreeSet, which stores the top MAX_HOT_KEYS categories with the largest local estimates in HotKey objects. TreeSet was chosen since it supports item insertion and deletion in logarithmic time. Workers emit these categories along with their sketches. The coordinator then uses this reduced set on the merged CMS to determine frequent categories, significantly improving performance.



This works because purchases are distributed randomly across the workers, which preserves relative frequencies in expectation. For instance, if there are 5 workers and a stream of 75 printers and 25 webcams, each worker is expected to receive 15 printers and 5 webcams. Thus, if printers are globally popular, they're expected to be locally popular and likely represented in a HotKey emitted by a worker

Testing

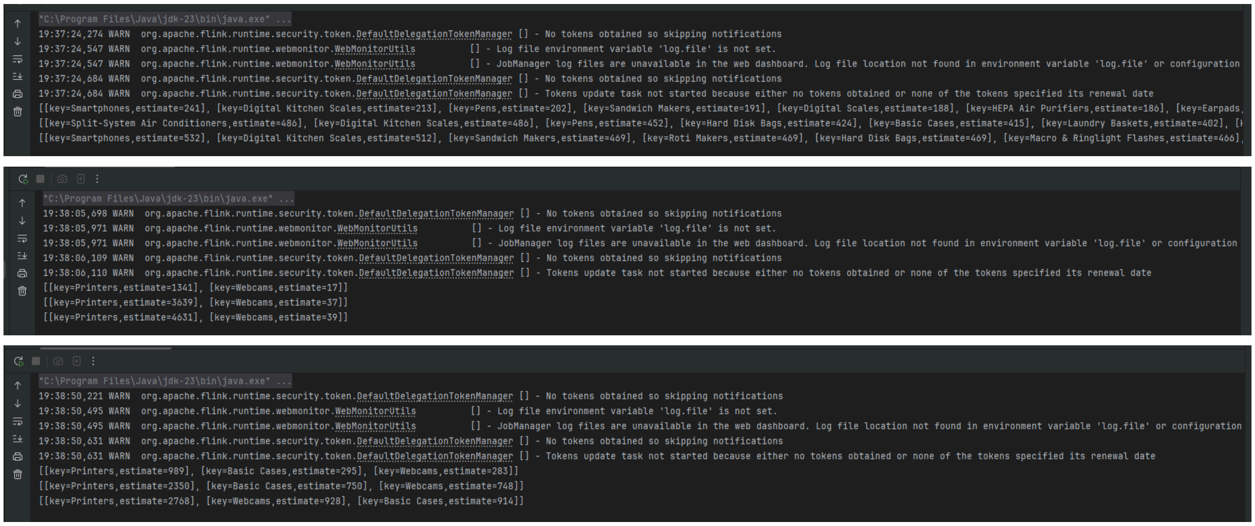
We tested our program by creating custom category distributions and observing the output. Below, we set "Webcams" and "Printers" to 25% each, meaning that of the ~200 categories, "Webcams" and "Printers" should appear as trending:



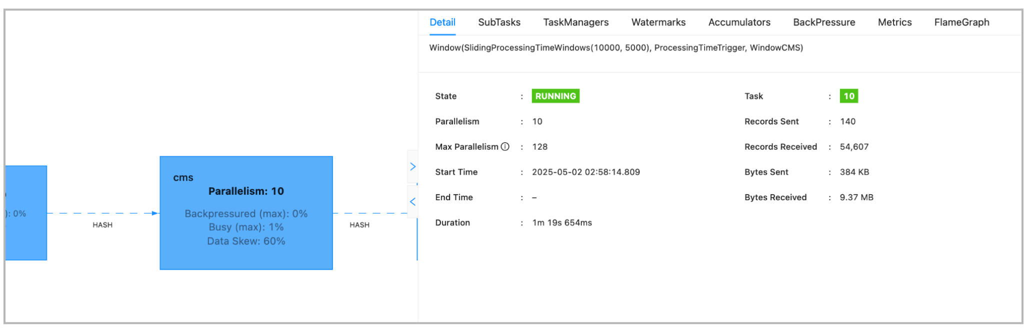
There are three test distributions included as YAML files in resources. To run a test, simply change the `WEIGHTS_FILE` variable in `distribution/CustomDistribution`.

1. test1.yaml: This file doesn't specify any categories, giving a uniform distribution.
2. test2.yaml: This file sets "Printers" to 99% and "Webcams" to 1%.
3. test3.yaml: This file sets"Printers" to 60%, "Webcams" to 20%, and "Basic Cases" to 20%.

For the above tests, if the program works properly, the relative frequencies should be reflected in the estimates for the popular categories reported by the program. The logs included show this is exactly the case:



We also used our Flink dashboard to verify the program's finer-grained qualities, such as load balancing between subtasks. To do this, we compared input/output rates of the subtasks for all states in the pipeline.

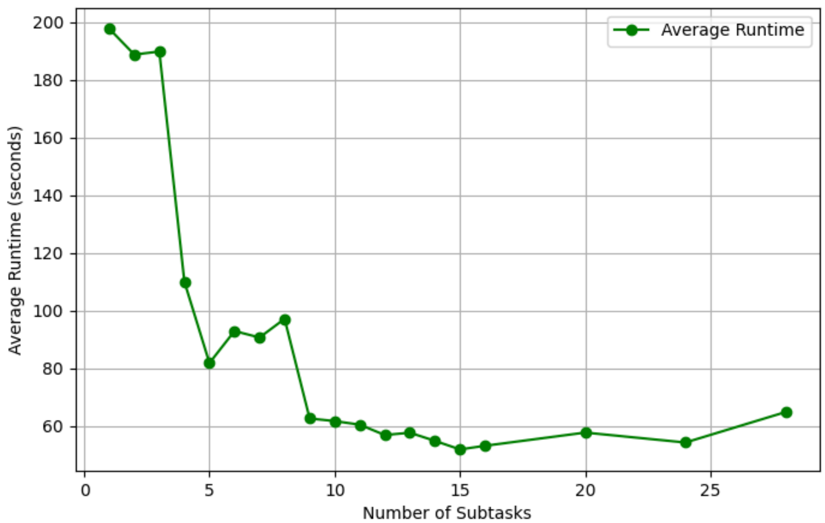


By running the sanity tests and looking at the dashboard, we were able to confirm that ourC CMS pipeline was accurately identifying popular categories and doing so in an evenly distributed manner across all subtasks.

Experimental Results

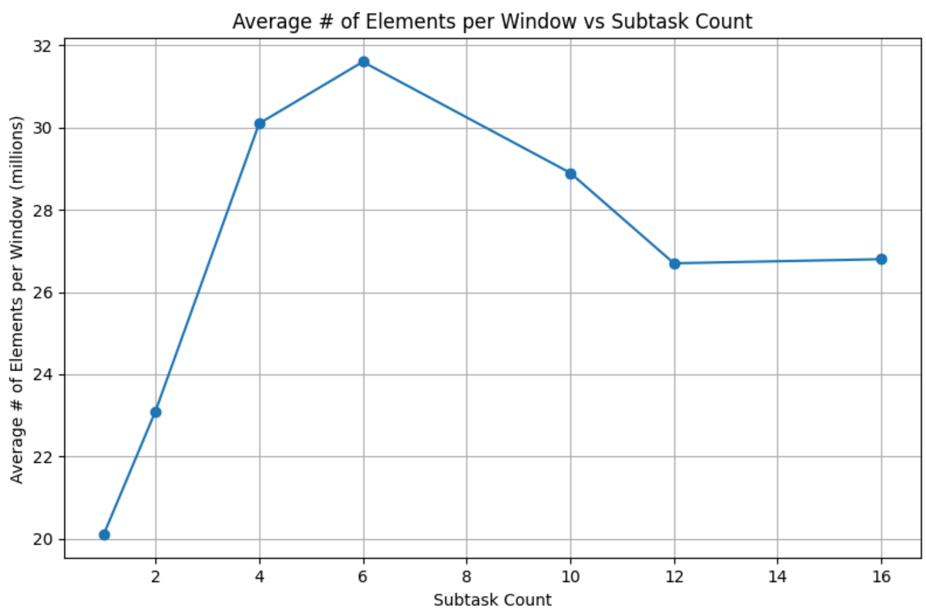
We conducted several performance experiments on our CMS processing pipeline. We ran each experiment three times and took the average metric. The system had 16 available cores and 8GB of allocated JVM heap memory throughout all of our testing.

The first was unrestricting the throughput rate of input elements and examining how the system performs under load. We allowed 100 million purchases to flow unrestricted and measured the runtime while varying subtask count. We found that more subtasks helped processing time with diminishing returns until multi-processing started diminishing capability at 16 cores, the number of physical cores available.



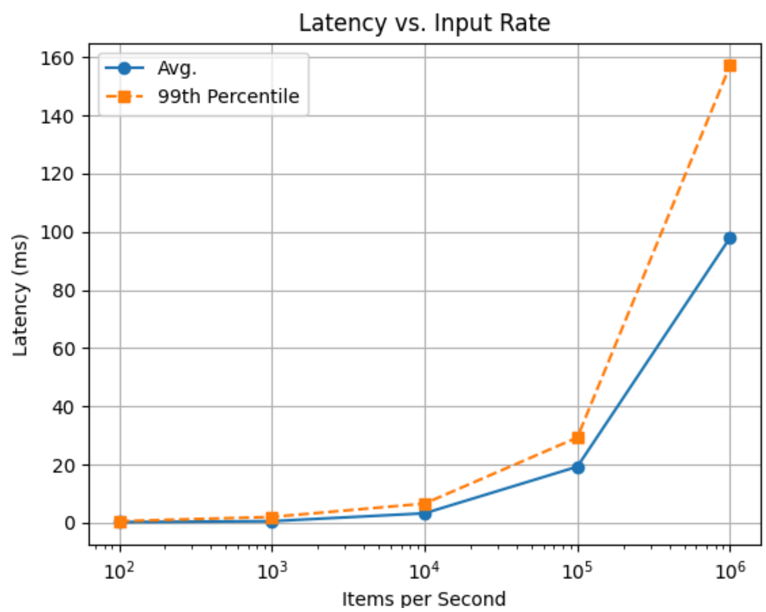
Our results suggest sharply diminished returns after 9 subtasks, most likely caused exhaustion of allocated memory due to increased stream buffering. While examining a system monitor, we observed heap usage close to 8GB while CPU-usage in percent remained stable at around 30% for subtask counts at or above 6. Additionally, performance degradation may stem from uneven load balancing, amplified by random assignment of elements to subtasks and by time-scheduling when subtasks counts are above available cores.

We also wanted to see the maximum throughput of elements a window could reliably ingest and analyze. We examined the throughput of one isolated 10-second window without observing the effects of buffering on subsequent windows. This measure isolates the effects from earlier stream build-up and highlights the increase in performance of having additional subtasks. The graph below displays the total number of elements streamed across all available subtasks per one time window.



This graph highlights an interesting relationship between intake rate and performance. We found that despite having a lower stream input rate, performance was better at higher thread counts (>10). This is due to each subtask processing fewer elements and potentially being unbalanced. The lower input rate for higher thread counts can also be attributed to a larger share of memory being reserved for CMS-arrays/other Java objects and the fact that memory is a bottleneck after 4-6 cores.

Lastly, we examined processing latency for 10 workers operating under varying stream input rates. Latency was measured as `finish - start` for each run of a worker's `WindowCMS` process. The graph below shows the results. The logarithmic scale on the x-axis means this is actually a linear relationship, suggesting the system scales well with input rate. When we tested on a stream without hard-coded rate limits (the hardware running the data source still imposes a natural rate limit), the latency peaked at around ~400 ms.



Overall, the main factor in reducing scalability is memory. We found that with more subtasks, we can increase performance at the cost of being able to buffer less elements per window. We expect that with more allocated memory, the runtime to resolve a bottleneck would continue to decrease.

Possible Improvements

There are four main areas that could be improved:

1. Implement other interesting distributions: Our data source allows distributions to be easily swapped. We could try distributions that more model natural popularity: exponential, geometric, etc.
2. Enhanced dashboard and metrics: Flink offers a host of graphs and analytics. We could experiment with custom graphs and views.
3. Automatic-scaling of nodes: For instance, we may need to process more nodes depending on time of day. Flink offers an Adaptive Scheduler for this purpose.

4. Checkpointing for fault tolerance: This is also supported by Flink, but there’s a lot to configure, including save locations, how many saves to retain, how often, concurrent checkpoints, etc.