ABSTRACT
All data is not equally popular. Often, some portion of data is more frequently accessed than the rest, which causes a skew in popularity of the data items. Adapting to this skew can improve performance, and this topic has been studied extensively in the past for disk-based settings. In this work, we consider an in-memory data structure, namely hash table, and show how one can leverage the skew in popularity for higher performance.

Hashing is a low-latency operation, sensitive to the effects of caching, branch prediction, and code complexity among other factors. These factors make learning in-the-loop especially challenging as the overhead of performing any additional operations can be significant. In this paper, we propose VIP hashing, a fully online hash table method, that uses lightweight mechanisms for learning the skew in popularity and adapting the hash table layout. These mechanisms are non-blocking, and their overhead is controlled by sensing changes in the popularity distribution to dynamically switch-on/off the learning mechanism as needed.

We tested VIP hashing against a variety of workloads generated by Wiscer, a homegrown hashing measurement tool, and find that it improves performance in the presence of skew (22% increase in fetch operation throughput for a hash table with one million keys under low skew, 77% increase under medium skew) while being robust to insert and delete operations, and changing popularity distribution of keys. We find that VIP hashing reduces the end-to-end execution time of TPC-H query 9, which is the most expensive TPC-H query, by 20% under medium skew.

1. INTRODUCTION
Hash tables are widely used data structures with a simple point lookup interface – mapping a key to a value. In database systems, they are used for in-memory indexing and also in query processing operations such as hash joins and aggregation. The lightweight computation involved and the constant time lookup guarantees are two reasons that enable hash tables to achieve high throughput when processing point queries.

However, not all keys contribute equally to the performance, and requests are often skewed towards a smaller set of “hot” keys. In multiple studies involving production workloads, fetch requests have been observed to follow the power law [17,20,30] where the popularity of keys exponentially decays with the rank. The Very Important key-value Pairs (VIPs) are the keys with lower rank, as they constitute a larger portion of requests and have a greater impact on the throughput. It is possible to further improve the throughput obtained from the hash table by leveraging this skew in popularity, as we show in our work.

Fig. 1 shows the core motivation behind VIP Hashing – giving more favorable spots to more popular keys. In the VIP configuration (Fig. 1b), the keys are ordered in descending order of popularity and the VIPs are in the front, analogous to seating VIPs in the front row for an event. By placing the popular keys at the start, they can be accessed faster due to multiple reasons such as fewer memory accesses and lesser computation (discussed in §4), which improves the overall throughput obtained from the hash table.

While attaining the VIP configuration is straightforward if the popularity of keys is known in advance (keys can be inserted in the right position in the chain according to their popularity), one might not have this information up front. Also, the popularity of the keys can change over time resulting in a different set of VIPs. Thus, more generally, one needs to learn the popularity of keys and adapt on the fly.

It is important to note that learning requires some amount of computation and storage. In case of disk-based data structures, this overhead can be relatively small compared to the high latency of accessing storage devices. However, this is not true for hash tables which are typically resident in memory and involve lightweight computation. Even adding a small counter per entry in the hash table can degrade per-
formance considerably, as we show in §5.4. Thus, the learning mechanisms need to be designed keeping the overhead in check compared to the gains.

Our contributions in this paper are as follows –

1. **Wiscer** ($\S4$) – We developed a configurable tool for measuring the performance of hash tables. Wiscer can be used to generate workloads with varying levels of skew in popularity, with different ratios of fetch, insert and delete operations, and shifting hot set of keys over time. To our knowledge, no existing benchmarking tool captures all of this behavior in one place.

2. **Roofline Analysis of the VIP configuration** ($\S4$) – We study the benefit of the VIP configuration (Fig. 1b) given prior knowledge of popularity. Since there is no overhead of learning, this analysis shows the maximum gain one can obtain from adapting to the skew (for a hash table with 10M keys at load factor 0.6, we observe a 57% increase in throughput from the VIP configuration in the best case).

3. **Learning on a budget** ($\S3$) – We developed lightweight mechanisms for learning the popularity distribution on the fly, adapting to the skew, sensing changes in the popularity distribution, and dynamically switching on/off learning to control the overhead. Put together, they give us the VIP Hashing method for learning the skew in popularity on the fly.

4. **Application to hash joins** ($\S6.1$) – We study the application of VIP hashing to PK-FK hash joins, and we obtain a 13-23% reduction in canonical join query execution time (for a cardinality ratio of 1:16 in the relations and a hash table with load factor of 1.4). We implemented VIP hashing in DuckDB [41] to speed up PK-FK hash joins in single-threaded mode, and we obtain a net reduction of 20% in end-to-end execution time of TPC-H query 9 [20] under low and medium skew.

5. **Application to point queries** ($\S6.2$) – Another common use of hash tables is processing point queries. We test VIP hashing at a load factor of 0.95 under a variety of workloads involving insert and delete operations, shifting popularity distribution, different rates of shift, etc. A gain in throughput of 22% (77%) is obtained under low (medium) skew, while our choice of parameters ensures that the loss due to the overhead of learning is capped in the worst case.

Overall, our experiments in §4 show that the VIP hashing is a fully online non-blocking learning method that captures the skew in popularity on the fly, while being robust to inserts, deletes, and shifting popularity distribution. We discuss related work in §7 and conclude in §8.

2. **BACKGROUND**

2.1 Hash Tables

A hash table [5] is an associative data structure that maps keys to values. In our work, we focus on chained hashing (hereafter referred to as hash table). A hash table (Fig. 1) uses a hash function to map each key to a unique index or bucket. Since more than one key can be mapped to the same bucket, the data structure resolves these collisions by maintaining a chain (linked list) of entries belonging to the bucket. The flexibility provided by this data structure for performing insert and delete operations, along with variable length keys and values make it a popular choice in many data systems [3, 18, 21].

2.1.1 On Properly Configuring the Hash Table

In this paper, we focus on hashing of 8-byte integer keys and values, which is a well studied problem in past research [28, 42]. It is important to configure the hash table correctly to draw reliable conclusions, and there are two important factors to consider. The first is the choice of the hash function. In our work, we use MurmurHash [15], which is a strong hash function that provides good collision resistance in practice. The second critical aspect is the load factor, which is the ratio of keys to the number of buckets in the hash table. Higher load factors correspond to fewer buckets, which lead to longer chains on average, whereas lower load factors require more buckets and consume more memory. Informed by parameter choices in popular open-source systems [3, 7, 21], we maintain a load factor between 0.5 and 1.5 to ensure that collisions are at an acceptable level while utilizing memory efficiently. Wherever applicable, we **rehash** the hash table to maintain this range of load factor. The number of buckets in the hash table are set to be a power of two, which is a common choice [17, 21] that speeds up the computation of the hash function. If the load factor exceeds 1.5 (falls under 0.5), we double (half) the number of buckets in the hash table.

2.2 Some Probability Bounds and Theorems

Below we discuss some tools related to probabilistic random variables that we use in our work.

- **Zipfian distribution**: We use Zipfian distribution [25] to model varying levels of skew in fetch operations issued to keys in a hash table. Zipfian distribution has been adopted by multiple studies in the past [29, 28, 14] to statistically model skew in popularity, as it captures the power law [17] characteristics of workloads that are often observed in practice [26, 30].

- **Estimating mean and variance**: Let $X$ be a random variable with mean $\mu$ and variance $\sigma^2$. Let $X_1, X_2, ..., X_n$ be $n$ independent and identically distributed (i.i.d.) measurements of $X$. The estimated mean $\hat{\mu}$ and estimated variance $\hat{\sigma}^2$ can be evaluated as

$$\hat{\mu} = \frac{\sum_{i=1}^{n} X_i}{n}, \quad \hat{\sigma}^2 = \frac{\sum_{i=1}^{n} X_i^2}{n} - \frac{\left(\sum_{i=1}^{n} X_i\right)^2}{n(n-1)}.$$
The popularity distribution shifts by a shift in popularity distribution occurs after every \( \text{distShiftFreq} \) operations. The zipfian factor of the popularity distribution. The pattern of keys to generate – total number of operations (fetch, inserts, etc.) to run on the hash table. Which storage engine to benchmark. Options are ChainedHashing (default), VIPHashing, and none (store workload to disk). The popularity rank of keys relative to the insertion order. Options are random (default) and sorted (where keys are inserted in increasing order of popularity; a.k.a. latest).

### 3. SKEWED WORKLOAD GENERATION WITH WISCER

#### 3.1 Overview

Wiscer is a workload generation tool that we propose in this paper. Wiscer has multiple configuration options (Table 1) that can be used to generate workloads with different levels of skew, varying proportions of fetch, insert, delete operations, different rates of popularity shift, etc. Below are some key features of Wiscer:

- **Level of skew**: Increasing levels of skew in the popularity distribution can be simulated by increasing the zipf factor. For instance, \( \text{zipf} = 0 \) and \( \text{zipf} = 4 \) correspond to uniform distribution and very high skew respectively (see Fig. 2).

- **Simulating popularity distribution shift**: The two related configuration options are \( \text{distShiftFreq} \) and \( \text{distShiftPrct} \). After every \( \text{distShiftFreq} \) fetch operations, the topmost popular keys that constitute \( \text{distShiftPrct} \) of the requests are randomly replaced by less popular keys. This simulates a behavior where keys in the hot set become less popular after some time, which has also been observed in some real-world workloads [26].

- **Gaussian tail bound confidence interval**: For a random variable \( X \) (refer above), the central limit theorem (CLT) [13] states that the error in estimated mean \( (\hat{\mu} - \mu) \) is approximately Gaussian distributed \( \mathcal{N}(0, \sigma^2/n) \). By applying the Gaussian pdf, a confidence interval can be obtained for the error \( (\hat{\mu} - \mu) \) as follows

\[
P(|\hat{\mu} - \mu| \leq t) \geq 1 - \exp\left(\frac{-nt^2}{2\sigma^2}\right) = \frac{L}{100}
\]

Thus, we can at least be \( L\% \) confident that the error \(|\hat{\mu} - \mu|\) is less than \( t \). Note that the confidence increases exponentially with \( n \) (number of samples \( X_i \), drawn). It is important to note that \( (\hat{\mu} - \mu) \) is only approximately Gaussian, so the confidence interval obtained from applying Gaussian tail bound is a heuristic.

#### 3.2 Experimental Configuration

All experiments in this paper are run on a Cloudlab machine with two 10-core Intel Xeon Silver 4114 CPUs with a peak frequency of 3.0GHz. The benchmarking process is pinned to a single core to avoid any overhead of context switching. The CPU scaling governor of the core has been set to performance, thus fixing the frequency to 3.0GHz at all times. The CPU has an L3 cache of 13.75MB, and the server machine has 192GB of RAM. This CPU belongs to the Skylake Intel architecture family [11], and the PMU’s hardware counters are programmed accordingly. The server machine is used exclusively for running Wiscer to mitigate interference from any concurrent processes.

### 4. ROOFLINE STUDY

In this section, we compare the performance of the Default and VIP configurations when the popularity of keys is static and known in advance. Since there is no overhead of learning involved in this case, this roofline study shows the maximum gain one can get from the VIP configuration for different levels of skew (4.2) in popularity at different load factors (4.3) of the hash table.

#### 4.1 Default vs VIP Configuration

**4.1.1 Motivation**

Fig. 3 shows an example of processing fetch requests in the Default and the VIP configurations. A key parameter to note is the displacement encountered, which is the total number of keys that were accessed to process the fetch.

| Option                      | Description                                                                 |
|-----------------------------|-----------------------------------------------------------------------------|
| zipf                        | The zipfian factor of the popularity distribution. \( \text{zipf} = 0 \) corresponds to uniform popularity. |
| initialSize                 | Initial number of keys in the hash table before running any operations.     |
| operationCount              | Total number of operations (fetch, inserts, etc.) to run on the hash table. |
| (fetch/insert/delete)       | Proportion of operations that are fetch/insert/delete.                      |
| Proportion                  | A shift in popularity distribution occurs after every \( \text{distShiftFreq} \) operations. |
| distShiftFreq               | The popularity distribution shifts by \( \text{distShiftPrct} \% \) every \( \text{distShiftFreq} \) operations. |
| distShiftPrct               | The popularity rank of keys relative to the insertion order. Options are random (default) and sorted (where keys are inserted in increasing order of popularity; a.k.a. latest). |
| storageEngine               | Which storage engine to benchmark. Options are ChainedHashing (default), VIPHashing, and none (store workload to disk). |
| keyPattern                  | The pattern of keys to generate – random (default) or sequential (1 to n).  |
| keyOrder                    | The random number generator is used to populate the hash table and generate the workload. |
| randomSeed                  | The seed value (unsigned integer) to initialize the random number generator (default = 0). |

Table 1: Configuration options supported by Wiscer
4.2 Impact of Increasing Skew

4.2.1 Workload

We compare the throughput of fetch operations in the Default and VIP configurations. We use Wiscer (Table 1) to generate fetch requests with increasing levels of skew \( \text{zipf} = 0 \text{ to } 5 \) in steps of 0.5) which are issued to a hash table with 10 million keys at a load factor of 0.6 \( (= 10^7 / 2^{24}) \). For each level of skew and hash table configuration, Wiscer is run with 10 distinct random seed values to populate the hash table and generate the workload. Each random seed results in a different arrangement of keys in the hash table. The popularity distribution is static, i.e., the rank of the keys remains the same throughout a run. One billion fetch requests are issued to the hash table for each random seed, and the data points reported in Fig. 4 are the median statistics over the 10 runs. We have run experiments on smaller (1M entries) and larger (100M entries) hash tables and found the trends to be similar.

4.2.2 Results

The results of this experiment are shown in Fig. 4. The gain in throughput ranges from 9%-57% depending upon the level of skew in popularity. Below we discuss our takeaways from the performance metrics measured using Wiscer:

- **Throughput**: The gap in performance between the VIP and the Default configuration increases up to \( \text{zipf} = 2 \) (medium skew), and gradually diminishes as the skew becomes very high (\( \text{zipf} = 4.5 \) or 5). This behavior is correlated with the hot sets becoming smaller as the skew increases and progressively becoming (L1/2/3) cache resident at different rates for the two configurations.

- **Displacement**: As expected, the displacement encountered in the VIP configuration is lower than the Default (see Fig. 3). For \( \text{zipf} = 1.5 \) and up, the total displacement becomes close to 1B (for 1B fetch requests), indicating that popular keys are at the front of their chains (displacement = 1) in the VIP configuration. For the Default configuration, the median displacement approaches 1B at higher levels of skew (\( \text{zipf} \geq 4 \)), but the variance is high as some random seeds can result in the popular keys placed further in the chains (however the likelihood of this happening is low as the load factor is not very high).

- **Instructions Executed**: The instructions executed are lower in the VIP configuration (up to 6% lower in the best case). The relative trend observed is similar to that of displacement, as the number of instructions executed is correlated with the number of keys accessed.

- **Cache misses**: The VIP configuration becomes L3 and L1 cache resident (at \( \text{zipf} = 2 \) and 2.5 respectively) more quickly compared to the Default configuration (at \( \text{zipf} = 3.0 \) and 4.5 respectively), which is expected as the hot set of the former is smaller than the latter (Fig. 5). At very high skew (\( \text{zipf} = 4.5 \) and 5), both the configurations are L1 resident and correspondingly, we do not observe much difference in the throughput. This indicates that caching has a big impact on the performance of hash tables.

Overall, we note that since the hot set of the VIP configuration is smaller than the Default, we encounter lower cache misses at all levels of cache. This contributes to the gain in performance we obtain from the VIP configuration.

Another important observation we make is that displacement indicates the goodness of the hash table configuration. The VIP configuration has lower displacement than the Default in all cases (in fact, the VIP configuration has the lowest possible displacement for a given data set, hash table size, hash function, and request skew; we discuss this in §5.2.3). We use this metric in building the mechanisms for sensing and dynamically switching-on/off learning (§5.2.3).
Fetch operation throughput

Displacement

Retired instructions

L1 cache misses

L2 cache misses

L3 cache misses

Figure 4: Relative performance of the VIP vs the Default configurations as the skew in popularity increases. One billion fetch requests are issued to a hash table with 10M keys (load factor 0.6) for varying levels of skew from $\text{zipf} = 0$ to $\text{zipf} = 5$. Each reported data point is the median over 10 runs with different random seeds. Percentage difference indicated at the top of each plot is the difference between median metrics of the VIP vs the Default configuration. The gain in fetch operation throughput varies with skew, and we obtain 53% increase in throughput for medium skew ($\text{zipf} = 2$). Lesser number of cache misses and instructions executed contribute to the gain obtained from the VIP configuration. Results are discussed in §4.2.2.

4.3 Impact of Increasing Load Factor

4.3.1 Workload

In this experiment, we increase the load factor while holding the size of the hash table constant. Similar to §4.2.1, we run one billion fetch operations on a hash table with $2^{24}$ buckets while varying the load factor from 0.5 to 1.5 in steps of 0.25 (this is achieved by increasing initialSize from $2^{23}$ to $3 \cdot 2^{23}$). Each configuration is run with 10 distinct random seeds and we compare the median statistics over the 10 runs.

4.3.2 Results

Fig. 5 shows the median gain obtained as we increase the load factor from 0.5 to 1.5. We obtain 1.6x, 2.6x, and 1.8x higher throughput from the VIP configuration at low ($\text{zipf} = 1$), medium ($\text{zipf} = 2$), and high skew ($\text{zipf} = 3$) respectively at load factor 1.5. In all cases, the gain from the VIP configuration increases as the load factor increases, which is expected as the likelihood of collisions is higher when more keys are present in the hash table. We find that the performance metrics of the VIP configuration are mostly stable (refer to Table 2) indicating a stable hot set size, while the performance of the Default configuration becomes steadily worse as the effective hot set grows larger with the load factor.

Table 2: Relative Metrics of VIP vs Default configuration as we increase the load factor ($lf$) at $\text{zipf} = 2$. The trends for low and high skew are similar.

| $lf$ | Throughput (fetch ops/s) | Avg. Displacement | L3 Misses | L1 Misses |
|------|--------------------------|-------------------|-----------|-----------|
| 0.5  | 235M us 188M (+25%)      | 1.0 vs 1.03 (-3%)  | 378M us 385M (-1.8%) | 380M us 412M (-8%) |
| 1    | 236M us 134M (+77%)      | 1.0 vs 1.17 (-15%) | 376M us 387M (-2.6%) | 380M us 436M (-13%) |
| 1.5  | 236M us 90M (+160%)      | 1.0 vs 1.62 (-38%) | 382M us 392M (-2.6%) | 382M us 458M (-17%) |

5. LEARNING POPULARITY ON-THE-FLY

In this section, we highlight the challenges of learning in-the-loop (§5.1), which motivated the lightweight mechanisms we built for VIP hashing. We describe how we learn, adapt, sense, and dynamically control the overhead on the fly (§5.2.3).
we observe a 66% loss in fetch operation through-

ble, such that the entries become 17 bytes long (8 byte key

demonstrate this behavior, we conduct a simple experiment

3.1 Learning In-the-Loop is Costly

Hash tables execute a tight loop of instructions – compute
the hash function, access keys in the bucket, and perform
required operations to process the request. Adding any
amount of additional computation or storage to this
loop can have a significant impact on the performance. To
demonstrate this behavior, we conduct a simple experiment
of adding a 1-byte requests counter per key in the hash table,
such that the entries become 17 bytes long (8 byte key
and value, and 1 byte counter).

We use Wiscer to compare the performance of the vanilla
implementation of hash table (16 byte entries) to the
implementation with request counters (17 byte entries). We
issue 500M fetch requests to a hash table with 1M entries
(load factor 0.95 = 10^8/2^32) for different levels of skew in
the popularity distribution (zipf = 0 to 5 in steps of 1). The
remaining configuration options of Wiscer are set to the
defaults (refer to Table 1). Fig. 6 shows the relative
performance of the two hash table implementations at
different levels of skew in the workload. There is a significant
loss in throughput ranging from 11-66% due to increase in
cache misses and instructions executed.

Counting requests is a fundamental requirement for learn-
ing the popularity distribution. However, this experiment
shows that even adding a small amount of additional mem-
ory can hurt performance significantly in the extreme case.
Thus, the challenge here is to work with a restricted “bud-
get” when learning in-the-loop, to balance the gains against
the overhead of learning.

5.2 VIP Hashing

From 5.1, we know that using additional memory and
computation can really hurt the performance of hash tables.
In this section, we describe how VIP hashing overcomes
these challenges by using lightweight mechanisms for learn-
ing and adapting to the popularity distribution (5.2.2).
while controlling the overhead by sensing and dynamically
switching-on/off learning as necessary (5.2.3). We first
give an overview of VIP hashing (5.2.1) followed by describing
the mechanisms used in detail (5.2.2-3).

5.2.1 Overview

Fig. 7 shows the VIP hashing method. At any given
time, there are three possible modes that the hash table
implementation can be in – learn+adapt, sense, and default
(vanilla). In the learn+adapt mode, the hash table learns the
popularity distribution and rearranges keys to move closer
to the VIP configuration. This mode is costly in terms of
both computation and storage, and we control how much
we run this mode by configuring the parameter NL. The
learn+adapt mode is run at the start, and subsequent trig-
gers of this mode happen only if the popularity distribution
changes, which is determined during the sense mode.

The sense mode is triggered after the learn+adapt mode
to measure some statistics (γB) that characterize the pop-
ularity distribution. These statistics require a total of 24
bytes of memory for the whole hash table (irrespective of
the size) and a few additional arithmetic operations in the
loop. Since the memory and computation footprint of this
mode is low, it does not add much overhead to the execu-
tion. The sense mode is run for NS requests at a time, and
is triggered periodically (every ND requests) to characterize
the popularity distribution at the time (γC). Comparing
the statistics (γB and γC) helps determine if the popularity dis-
tribution has changed, and informs the decision of whether
to switch on learning.

The default mode is the vanilla implementation of chained
hashing (2.1) with 16 byte entries. There is no additional
overhead of storage or computation. This mode is run most
of the time (ND > NL, NS), so the performance is close to
the vanilla implementation of hash table in the worst case.

In the following sections, we discuss the mechanisms we
use for the learn+adapt (5.2.2) and sense (5.2.3) modes.
We discuss our choice of parameters (NL, NS, ND, etc.) in
5.3, that allow us to balance the performance gains against
the overhead of learning.

5.2.2 Learning & Adapting

Algorithm 1 describes how we learn the popularity distri-
bution and adapt to the skew on the fly. The popularity of
a key is estimated as the proportion of requests made to the
key (5.2.3). Thus, learning the popularity distribution re-
quires counting requests, which we know is challenging from
the discussion in 5.1.

To overcome the challenge of counting requests in-the-
loop, we perform two optimizations. First, we count re-
quests in a separate data structure that mimics the hash ta-
ble in arrangement (for every entry in the hash table, there
is a corresponding entry in the request counting hash table).
Although this temporarily requires more memory (about 50-
60% increase in memory usage depending on the load factor)
than maintaining a counter per key in the hash table, the
Figure 7: Overview of VIP Hashing. At any time, the hash table is in one of the three modes – learn+adapt, sense, or default. The amount of time spent on learning and adapting is limited since it is costly. The popularity distribution is sensed periodically to detect changes and trigger learning only when necessary.

Algorithm 1 Learning and Adapting on-the-fly

1: procedure FETCHADAPTIVE(requests)
2:     ht ← getHashTable()
3:     /* Requests are counted in a separate data structure*/
4:     req_cnt_ht ← getRequestsCountingHashTable()
5:     for r in requests do
6:         hash ← murmurHash(r.key)
7:         ht_entry ← ht[hash]
8:         req_entry ← req_cnt_ht[hash]
9:         /* Keep track of entry with minimum requests */
10:        min_req_ht_entry = ht_entry
11:        min_req_entry = req_entry
12:        while ht_entry and ht_entry.key ≠ r.key do
13:            if min_req_entry.count < min_req_entry.count then
14:                min_req_entry = req_entry
15:                min_req_entry = req_entry
16:                ht_entry = ht_entry.next()
17:                req_entry = req_entry.next()
18:            if ht_entry == null then
19:                r.found = false
20:                continue
21:            r.found = true
22:            r.value = ht_entry.value
23:            req_entry.count = req_entry.count + 1
24:            if req_entry.count > min_req_entry.count then
25:                /* Swap this entry with the minimum requests entry */
26:                swap(ht_entry, min_req_ht_entry)
27:                swap(req_entry, min_req_entry)
28:        /* Reclaim cache space by clearing req_cnt_ht */
29:        clearCache(req_cnt_ht)

cost is incurred only during the learn+adapt mode. Second, at the end of the learn+adapt mode, we clear the request counting hash table (req_cnt_ht) from the cache by issuing cache flush instructions (_mm_clflushopt on Intel CPUs[8]), thus restricting the cache pollution caused by the additional data structure to learn+adapt mode.

To attain the VIP configuration, we need to sort the keys in descending order of popularity in the bucket chains. Given that the proportion of requests made to a key is an estimate of popularity, we use Algorithm 1 to stochastically sort the keys in descending order of requests received on the fly. When performing a fetch operation, we keep track of the entry with minimum requests (min_req_ht_entry) encountered in the path to the entry being fetched. If the entry being fetched has received more requests, then it is swapped with the min_req_ht_entry and it moves forward in the chain. We propose the following theorem:

THEOREM 1. Let there be a bucket chain with n keys K1, K2, ..., Kn which have popularity p1 > p2 ... > pn > 0. Let the keys be in a random order in the chain. Then, by applying Algorithm 1, the keys will converge to the sorted order of popularity as number of fetch requests N → ∞.

We formally prove this theorem in Appendix A. There are two properties of Algorithm 1 that are worth noting. First, the VIPs move to the front quickly, as they can skip over multiple entries in the chain in a single fetch request. This algorithm is, in essence, similar to selection sort as we are moving the entry with minimum requests to the end of the (sub)-chain being accessed. An alternative would be to compare only adjacent keys (bubble sort), which empirically requires more requests for a VIP to move to the front.

Second, the cost of swapping is amortized, as there is at most one swap performed per fetch operation. This approach is faster compared to performing a full sort on every request, or sorting at the end after counting requests for some time (we will have to access all the buckets in order to perform a full sort; this will incur cache misses and also pollute the cache).

5.2.3 Sensing & Dynamically Switch-on/off Learning

Algorithm 2 describes how we sense some key statistics of the popularity distribution, which enable us to dynamically switch-on learning only when the distribution has changed (Algorithm 3). While there are multiple ways to quantify the difference between two probability mass functions (pmfs)[0][1][2][24], we choose a lightweight statistic to compare distributions – average displacement. In §4.2.2, we saw that displacement encountered indicates the “goodness” of the hash table configuration. Every popularity distribution imposes a pmf over the displacement encountered on a request, which is a derived random variable. Formally stated:

AXIOM 1. Let K1, K2, ..., KN be N keys in the hash table with popularity p1, p2, ..., pN (p1 + p2 + ... + pN = 1) at displacement d1, d2, ..., dN (di ≤ N). Let D be the random variable of the displacement encountered on a successful fetch request. Then,
Algorithm 2 Sensing

1: procedure FETCHSENSING(requests)
2: \(ht \leftarrow \text{getHashTable}()\)
3: /* Metrics to track */
4: \(\text{disp} \leftarrow 0\) \quad \triangleright \text{cumulative displacement}
5: \(\text{disp}_\text{sq} \leftarrow 0\) \quad \triangleright \text{cumulative square}
6: count \leftarrow 0 \quad \triangleright \text{number of requests}
7: \(c = 0.95\) \quad \triangleright \text{confidence level of the interval}
8: \[\text{for } r \text{ in requests do}\]
9: \(\text{hash} \leftarrow \text{murmurHash}(r.key)\)
10: \(ht\_entry \leftarrow ht[\text{hash}]\)
11: \(d \leftarrow 1\)
12: \[\text{while } ht\_entry \text{ and } ht\_entry->key \neq r.key \text{ do}\]
13: \(ht\_entry = ht\_entry.next()\)
14: \(d = d + 1\)
15: \[\text{if } ht\_entry == \text{null then}\]
16: \(r.found = \text{false}\)
17: \(\text{continue}\)
18: \(r.found = \text{true}\)
19: \(v = ht\_entry.value\)
20: \(\text{count} = \text{count} + 1\)
21: \(\text{disp} = \text{disp} + d\)
22: \(\text{disp}_\text{sq} = \text{disp}_\text{sq} + d \times d\)
23: /* Estimating mean, variance v, and C.I. width w*/
24: \(u = \text{disp}/\text{count}\)
25: \(v = \text{disp}_\text{sq}/(\text{count} - 1) - \text{disp}^2/(\text{count} \times (\text{count} - 1))\)
26: \(w = \sqrt{-2\cdot v\cdot \log(1-c)/\text{count}}\) \quad \triangleright \text{Gaussian tail bound}
27: \(\gamma = (u, w)\)
28: \(\text{return } \gamma\)

\[P(D = d) = \sum_{i=1}^{N} p_i \cdot \mathbb{1}_{d_i = d}\]

i.e, the probability that displacement \(d\) is encountered on a successful fetch request is the probability that any of the keys with displacement \(d\) were fetched. The average displacement is calculated as

\[\mu_D = E[D] = \sum_{i=1}^{N} i \cdot P(D = i)\]

We make the following observation:

**Axiom 2.** The VIP configuration minimizes \(E[D]\) over all possible arrangements of keys in the hash table for a fixed load factor, popularity distribution, and hash function.

The VIP configuration orders keys by popularity, thus giving more “weight” to lower values of \(D\) which minimizes the average displacement. It is straightforward to see that for a given hash table configuration, two popularity distributions with different average displacement will not be identical (although the opposite is not true). Thus, a change in average displacement reflects a shift in the popularity distribution.

The parameters we learn from sensing are \(\gamma = (\hat{\mu}_D, \hat{w}_D) = (u, w)\) (Algorithm 2), where \(\hat{\mu}_D\) is the estimated average displacement, and \(\hat{w}_D\) is the width of the confidence interval around \(\hat{\mu}_D\) obtained using Gaussian tail bounds (2.2). We estimate the average displacement as

\[\hat{\mu}_D = \frac{\sum_{i=1}^{N_S} D_i}{N_S}\]

Algorithm 3 Dynamically Switch-on/off Learning

1: procedure HASDISTRIBUTIONCHANGED(\(\gamma_B, \gamma_C\))
2: \((u_B, w_B) = \gamma_B\)
3: \((u_C, w_C) = \gamma_C\)
4: \[\text{if } |u_B - u_C| > |u_B + w_B| \text{ then}\]
5: \(\text{return } \text{true}\)
6: \(\text{else}\)
7: \(\text{return } \text{false}\)

which is the sample mean\(^1\) of displacement encountered \(D_i\) (\(1 \leq i \leq N_S\)) over \(N_S\) fetch requests in the sense mode. Similarly, we also estimate sample variance \(\hat{\sigma}_D^2\) (2.2).

We further characterize the pmf by building a confidence interval using Gaussian tail bounds (2.2). The width \(\hat{w}_D\) of the interval at confidence level \(c\) (\(c = 0.95\) in our experiments) is calculated as

\[\hat{w}_D = \sqrt{-2 \cdot \hat{\sigma}_D^2 \cdot (1-c)} \frac{1}{N_S}\]

Note that \(\hat{\sigma}_D\) is estimated variance from a sample of \(N_S\) observations, and \((\hat{\mu}_D - \mu_D)\) only approximately Gaussian according to CLT (2.2). Thus, the width \(\hat{w}_D\) obtained by applying Gaussian tail bounds is a heuristic.

We switch-on learning (Algorithm 3) only if we detect a significant change in the average displacement. Given two sets of parameters \(\gamma_B = (u_B, w_B)\) and \(\gamma_C = (u_C, w_C)\) where \(u_B\) and \(u_C\) are estimated means, we check if the confidence intervals are disjoint. If so, then heuristically with a probability \(c^2 = (0.95)^2 = 0.9\), we can be sure that the real means are not equal and the distributions have diverged. Thus, we detect changes in popularity distribution in a non-intrusive manner by computing lightweight statistics.

5.3 Parameters

The parameters \(N_L, N_S, \text{and } N_D\) determine how long the hash table runs in learn+adapt, sense, and default modes respectively. Our goal is to choose these parameters such that the gains of learning are balanced against the overhead.

Our choice of parameters is general, made using theoretical and empirical evidence that is independent of the popularity distribution. Thus, our techniques (5.2) apply to any distribution with skew irrespective of its specific properties. Note that it is possible to further tune the parameters and the techniques with additional knowledge such as total number of requests, patterns in the workloads, family of distribution, etc.

5.3.1 Allocating the budget for learning – \(N_L\) vs \(N_D\)

Learning in-the-loop is costly – in our experiments, we find that the learn+adapt mode can be as much as 4x slower than the vanilla implementation in the worst case under no skew (we tested different hash table sizes from 1M to 100M keys). If a total of \((N_L + N_D)\) requests are issued to VIP hashing, the loss in throughput due to learning would be:

\[1 - \frac{T_{\text{vanilla}}}{T_{\text{vip}}} \leq \frac{1 - \frac{N_D}{N_D + N_L}}{1 - \frac{N_D}{N_D + N_L} + \frac{N_L}{N_D}}\]

assuming that the vanilla implementation takes time \(t\) on an average to process each request. We cap the overhead of

\(^1\)Note that instead of sampling, we could also use the request counting data structure \(\text{reqcntht}\) in (5.2.2). However, this would incur cache misses and also pollute the cache affecting performance (5.1).
learning to at most 5% by choosing \( N_D = 60 \cdot N_L \) in our experiments (i.e., learn+adapt mode is run for at most \( \frac{1}{60} \) of the total requests). More generally, the cap on overhead is \((1 - \frac{61}{60} + \delta)\), where \( \delta \) depends on the experimental configuration (\( k = 4 \) on our hardware). Thus, fixing a budget for \( N_L / N_D \) limits the overhead of learning in the worst case.

5.3.2 Choosing \( N_L \) – how much to learn?

The learn+adapt mode is run for \( N_L \) requests at a time. Our goal is to capture the popularity distribution as much as possible while learning for a finite number of requests. From previous work \cite{Avrachenkov2005}, we know that it takes \( \Theta(N) \) i.i.d.

samples to learn a probability mass function over \( N \) items (with error \( \epsilon = 1 \) in KL divergence compared to the true pmf).

When the cardinality of the hash table is not known/can vary, we choose \( N_L = 1.5 \cdot \text{htsize} \), i.e., \( 1.5 \) times the number of buckets in the hash table. Since we maintain a load factor of at most 1.5 at all times, the number of keys in the hash table \( N \leq 1.5 \cdot \text{htsize} \), which satisfies our requirements.

5.3.3 Parameters for sensing – \( N_s \) and \( c \)

We sense the distribution for \( N_s \) requests at a time to estimate the average displacement \( \hat{\mu}_c \) and build an interval with confidence \( c \). Since the load factor is low and the longest chain length is likely to be low as well (except in pathological cases where many keys are hashed to the same bucket), we have found that choosing \( N_s \) to be a large number (1000) has been sufficient in our experiments. We build a \( c = 95\% \) confidence interval that heuristically gives us a probability of \( c^2 = (0.95)^2 = 0.9 \) when we detect a shift in popularity. By increasing (decreasing) the confidence level, we can be less (more) sensitive to changes in popularity.

6. APPLICATIONS

6.1 PK-FK Hash Joins

Hash tables are frequently used in database systems for processing join queries. In this section, we describe how VIP hashing can improve the performance of primary key-foreign key (PK-FK) joins in the presence of skew.

6.1.1 Experimental Setup

Motivated by past research \cite{zipf2003,zipf2004,zipf2005}, we consider the canonical PK-FK join query on tables \( R \) and \( S \) (\(|R| : |S| = 1 : 16\)) with 8-byte integer attributes (16-byte tuples). Skew can arise in PK-FK relations \cite{zipf2003,zipf2004,zipf2005} when some keys occur more frequently than others in the outer relation \( S \). We use Wiser to instantiate \( R \) and \( S \) using the sequential key pattern for primary keys in \( R \), and varying the level of skew in the outer relation \( S \) from uniform (\( \text{zipf}=0 \)) to high (\( \text{zipf}=3 \)) for 10 distinct random seeds. We compare the performance of the canonical hash join algorithm \cite{zipf2003,zipf2004,zipf2005} implemented using the default and VIP hash tables, while materializing pointers to output tuple pairs. We assume that the tuples in \( S \) are i.i.d., i.e., the popularity distribution is static. We explore effects of dynamic popularity distribution in §6.2.

6.1.2 Default vs VIP Hash Join

Fig. 8 shows the relative execution time of the default vs VIP hash join implementations. The cardinalities of \( R \) and \( S \) are 12M and 192M respectively (\(|R| : |S| = 1 : 16\)) \cite{zipf2003,zipf2004,zipf2005}, and the load factor is 1.4 (= 12 \cdot 10^6 / 2^{23}). For medium skew in the outer relation, the average displacement encountered by the default hash join implementation is 1.23 (Table 3).

For the case of canonical hash join query, the learning budget of the VIP hash table implementation can be calculated in advance while maintaining \( N_L : N_D = 1 : 60 \) \cite{zipf2003,zipf2004,zipf2005} since we almost always know the cardinalities of the relations from system catalogs. Learning is triggered at the beginning of the probe phase with a budget of \( N_L = \min(|R|, \frac{|S|}{60}) = 16\cdot|R| \cdot 0.26 \cdot |R| \) lookups from the outer relation. Learning takes about 3% of the total execution time, ranging from 70-600ms depending on the level of skew. Note that the average displacement of the VIP hash join implementation is very close to 1 (Table 3) indicating that the learning mechanism efficiently captures the popularity distribution, and reduces cache misses and instructions executed.

To show the impact of varying the learning budget, we repeated the experiments for lower and higher cardinality ratios. For a ratio of 1 : 4, we have a learning budget of \( 4 \cdot |R| = 0.07 \cdot |R| \) requests and the overall reduction in execution time is 18.6%. On the other hand, a cardinality ratio of 1 : 64 allows a learning budget of \( |R| = \min(16\cdot|R|, \frac{64}{61}) \) and results in 25.8% reduction in execution time. Thus, the available learning budget impacts the gain in performance.

6.1.3 Application to Skewed TPC-H

We focus our attention on TPC-H query 9 \cite{tpc-h}, which is the most expensive TPC-H query involving multiple PK-FK join operations. We implemented VIP hashing in DuckDB \cite{duckdb}, an in-memory vectorized DBMS, to speed up PK-FK hash join.

\footnote{Note that the average displacement is low for the default configuration in this case, since the keys are sequential. Holding the load factor constant, randomly generated keys result in a median (over 10 random seeds) average displacement of 1.48.}
6.2 Point Queries

Another common use of hash tables is for in-memory indexing in database systems \cite{4,14} and in key-value stores \cite{3,6}. For processing point queries. In this section, we evaluate VIP hashing against a range of workloads generated using Wiscer that highlight the robustness of our techniques for learning in-the-loop under different conditions. In all the experiments, we assume no prior knowledge of the characteristics of the request distribution. The first two workloads (§6.2.1, §6.2.2) involve fetch operations, and the last two (§6.2.3, §6.2.4) perform insert and delete operations.

We run these workloads on a hash table with 1M entries (load factor $0.95 = 10^6 / 2^{20}$) in the Default configuration at the start. Each of these workloads issues 500M operations to the hash table at varying levels of skew ranging from uniform ($zipf = 0$) to medium skew ($zipf = 2$). The remaining configuration options of Wiscer are set to the defaults (refer to Table 1). We compare the performance of VIP hashing to the default hash table in Fig. 10-14.

6.2.1 Static Popularity

In this workload, the popularity of keys in the hash table remains the same throughout the experiment. We run 500M fetch operations at four levels of skew from $zipf = 0$ to $zipf = 2$ in steps of 0.5. For the case of uniform popularity distribution ($zipf = 0$), the overall loss in throughput is 2% (Fig. 10a) which is within our allocated budget of 5% (§5.3.1), whereas for low skew ($zipf = 1$), we obtain a net gain of 22% (Fig. 10b). The performance gain is higher at medium levels of skew — the gain in throughput at $zipf = 1.5$ and $zipf = 2$ is 77% (Fig. 10c) and 116% (Fig. 10d), respectively. Since the popularity distribution is static, the learn+adapt mode is triggered only at the start of the experiment for $1.5 \cdot \text{htsize}$ requests in all cases. The periodic runs of the sense mode do not detect a change in popularity and the learn+adapt mode is not triggered again. Thus, learning is run only when necessary, and the overhead of VIP hashing is minimized.

6.2.2 Popularity Churn

In this workload, we study how VIP hashing adapts to changing popularity distribution over time. We simulate two rates of shift — medium and high. For the case of medium churn, the popularity distribution shifts by 25% every 100M fetch operations (about 3s at $zipf = 1$). Fig. 11 shows the behavior of VIP hashing under medium churn. Note that the sense mode triggers learning only when necessary. For instance, learning was triggered 3 out of the 4 times at $zipf = 1$ only when there was a substantial change in average displacement due to shift in popularity (accompanied by a decrease in performance). The gain in throughput for $zipf = 1$ and $zipf = 1.5$ is 19% and 49% respectively.

For the case of high churn (Fig. 12), the popularity distribution shifts by 50% every 10M fetch operations ($< 1s$), i.e., popularity shift occurs 50 times during the experiment. Every run of the sense mode detects a change in distribution and learning is triggered every time for both levels of skew. We obtain a net increase of 12% and 22% in throughput for $zipf = 1$ and $zipf = 1.5$ respectively. Thus, VIP hashing is able to sense changes in the distribution, and re-learn on the fly.

6.2.3 Steady State

Next, we test a workload with 98% fetch requests, 1% insert requests, and 1% delete requests (Fig. 13). The cardinality of the hash table doesn’t change substantially during the experiment, as the number of insert and delete operations are approximately balanced. The keys are inserted (deleted) in random positions of the popularity order. We observe that as new keys (which are less popular with high probability) are inserted at the front of the chains, the hash table arrangement steadily becomes worse and the performance of VIP hashing approaches the default for $zipf = 1$. At $zipf = 1.5$, the trend is similar, but is less stable as a small number of topmost keys carry most of the popularity weight. A change in average displacement is sensed every time and learning is triggered, which bounces back the performance of VIP hashing. We obtain a net gain in throughput of 5.4% and 3% for $zipf = 1$ and $zipf = 1.5$ respectively.

6.2.4 Read Mostly

In this workload, we issue 98% fetch requests and 2% insert requests. New keys are inserted in arbitrary positions in the popularity order. Similar to §6.2.3, we observe that the performance steadily becomes worse as new keys are inserted at the front of the bucket chains for $zipf = 1$ (Fig. 14a). Inserting new keys increase the load factor, which degrades the throughput of the default implementation as well (Fig. 14a). The rate of degradation at $zipf = 1.5$ as the popularity weight lies with a smaller portion of topmostly keys. Rehashing is triggered when the load factor exceeds 1.5 (happens every 75·htsize requests), which bounces back the performance for both the default and VIP hashing implementations for both levels of skew. The periodicity at which sensing is triggered (every 90·htsize requests) increases every time rehashing is performed, as we update the parameters $N_b$ and $N_d$ according to the size of the hash table (htsize). Given that the change in the distribution is substantial, every run of the sense mode detects a change in popularity and triggers learning. The net gain in throughput for $zipf = 1$ and $zipf = 1.5$ is 1% and 11% respectively.
(a) Static popularity (§6.2.1) with $\text{zipf}=0$ (uniform distribution). Since there is no skew in popularity, no performance gain can be obtained from VIP hashing. Learning adds overhead to VIP hashing (4x slower), and is only triggered at the start for $(1.5\cdot2^{20})$ requests (0.3s). Subsequent sensing of the popularity distribution does not detect any change, and learning is not triggered. Total loss in throughput is 1.9%, which is within our allocated budget.

(b) Static popularity (§6.2.1) with $\text{zipf}=1$ (low skew). Learning is only triggered at the start and is 3x slower than the default (0.13s vs 0.05s respectively). Sensing does not detect any changes to the popularity distribution, so learning is not triggered again. The overhead of learning is offset by the gain in performance from the VIP configuration. We observe an overall increase in throughput of 21.8%.

(c) Static popularity (§6.2.1) with $\text{zipf}=1.5$ (medium skew). Learning is only triggered at the start for 0.03s, and subsequent triggers of sense mode do not detect any changes to popularity. A net gain of 76.5% in throughput is observed.

(d) Static popularity (§6.2.1) with $\text{zipf}=2$ (medium skew). Learning is only triggered at the start for 0.02s, and subsequent triggers of sense mode do not detect any changes to popularity. A net gain of 116.1% in throughput is observed.

Figure 10: Performance of VIP hashing under static popularity distribution at increasing levels of skew ranging from $\text{zipf}=0$ (uniform distribution) to $\text{zipf}=2$ (medium skew). Fetch requests are issued to a hash table with 1M entries at load factor 0.95 with keys in a random order initially. Learning is only triggered at the start and the performance gain ranges from 22% to 116% depending on the level of skew. The overhead of VIP hashing in the case of uniform distribution ($\text{zipf}=0$) is 2%, which is within our allocated budget.

(a) Medium churn rate (§6.2.2) with $\text{zipf}=1$. Sensing triggers learning 3 times, when it detects a significant difference in average displacement. Throughput increases by 18.9% overall.

(b) Medium churn rate (§6.2.2) with $\text{zipf}=1.5$. Sensing triggers learning only 1 time, when it detects a significant difference in average displacement. Throughput increases by 49.0% overall.

Figure 11: Performance of VIP hashing under medium popularity churn at $\text{zipf}=1$ and $\text{zipf}=1.5$. Fetch requests are issued to a hash table with 1M entries at load factor 0.95 with keys in a random order initially. Popularity distribution shifts every 100M requests by 25% (top 21 out of 1M keys at $\text{zipf}=1$, and the topmost key at $\text{zipf}=1.5$, are replaced by less popular key(s) at random). Distribution shift increases average displacement and can reduce performance (notice drop in performance of VIP hashing at 400M requests for $\text{zipf}=1.5$). Sensing triggers learning whenever it detects a significant increase in average displacement. Net increase in throughput for $\text{zipf}=1$ and $\text{zipf}=1.5$ is 19% and 49% respectively.

2 The triggers of sense mode and learn+adapt mode have been marked using green circles and orange squares respectively. The unmarked periodic dips in throughput for both the VIP and default implementations are due to monitoring activity performed by the Cloudlab environment, and are unrelated to VIP hashing.
Learning+ 
Adapting
Periodic Sensing
....
Popularity
Distribution shifts

(a) High churn rate ($\S$ 6.2.2) with $\text{zipf} = 1$. Overall, 11.8% increase in throughput is observed.

(b) High churn rate ($\S$ 6.2.2) with $\text{zipf} = 1.5$. Overall, 21.9% increase in throughput is observed.

Figure 12: Performance of VIP hashing under high popularity churn at $\text{zipf} = 1$ and $\text{zipf} = 1.5$. Fetch requests are issued to a hash table with 1M entries at load factor 0.95 with keys in a random order initially. Popularity distribution shifts every 10M requests by 50% (top 750 out of 1M keys at $\text{zipf} = 1$, and the top 2 keys at $\text{zipf} = 1.5$, are replaced by less popular keys at random). The benefit of learning diminishes as the popularity order becomes shuffled. Periodic sensing triggers learning every time, as frequent distribution shifts cause significant change in average displacement. Net increase in throughput for $\text{zipf} = 1$ and $\text{zipf} = 1.5$ is 12% and 22% respectively.

Learning + 
Adapting
Periodic Sensing
....
Rehashing

(a) Steady state ($\S$ 6.2.3) with $\text{zipf} = 1$. An overall gain of 5.4% is observed.

(b) Steady state ($\S$ 6.2.3) with $\text{zipf} = 1.5$. An overall gain of 3.1% is observed.

Figure 13: Performance of VIP hashing in a steady state consisting of 98% fetch requests, 1% insert requests, and 1% delete requests at $\text{zipf} = 1$ and $\text{zipf} = 1.5$. 500M fetch requests are issued to a hash table with 1M entries at load factor 0.95 with keys in a random order initially. With new keys being inserted at the front of the buckets and existing keys being deleted, the hash table arrangement steadily becomes worse. Periodic sensing triggers learning every time which bounces back the performance. The net throughput gain for $\text{zipf} = 1$ and $\text{zipf} = 1.5$ is 5% and 3% respectively.

Learning + 
Adapting
Periodic Sensing
....
Rehashing

(a) Ready mostly workload ($\S$ 6.2.4) with $\text{zipf} = 1$. Overall, we observe a gain of 1% in throughput.

(b) Ready mostly workload ($\S$ 6.2.4) with $\text{zipf} = 1.5$. Overall, we observe a gain of 10.6% in throughput.

Figure 14: Performance of VIP hashing under a ready mostly workload with 98% fetch requests and 2% insert requests at $\text{zipf} = 1$ and $\text{zipf} = 1.5$. 500M fetch requests are issued to a hash table with 1M entries at load factor 0.95 with keys in a random order initially. For this workload, rehashing is triggered when the load factor reaches 1.5, which happens every $75 \cdot \text{htsize}$ requests. Whenever rehashing occurs, we double the periodicity of sensing ($N_S$) and the duration of learning ($N_L$), i.e., learning is triggered less frequently for longer duration each time. The net gain in throughput for $\text{zipf} = 1$ and $\text{zipf} = 1.5$ is 1% and 11% respectively.
7. RELATED WORK

Hash tables are well studied data structures in literature. Two major categories of hash tables are chained hashing \[5\] where collisions are resolved by chaining \([2,1]\), and open addressing \([16]\) where collisions are resolved by searching for alternate positions in an array. Richter et al. \[42\] study different hash table implementations spanning both the categories, hash functions, workload patterns, etc. while highlighting the variability in the performance of hash tables based on a host of factors. Similar to our work, they consider the problem of hashing 8-byte integer keys and values.

Multiple open source hash tables \([2,10,19]\) use both categories of implementations. For instance, Google’s flat hash table \(19\) takes an open addressing approach, while the bytell (byte linked list) hash table \(2\) uses chaining to resolve collisions. When it comes to data systems, DBMS such as SQLite3 \(18\) and PostgreSQL \(7\), as well as key-value stores such as Redis \(1\) and Memcached \(21\) use data structures that involve chaining of entries. Thus, we find that chained hash tables are a popular choice commonly used in practice.

Skew in popularity is a well studied phenomenon. Multiple studies involving production workloads have found fetch requests to follow a power-law behavior \([26,30]\), which is often captured using the zipfian distribution \([28,43,11]\). For instance, the request distribution in the core workloads of YCSB \(23\) is zipfian by default. Alongside skew in popularity, previous work \([26]\) also discusses effects such as churn in popular keys in real world workloads. This is a key feature captured by Wiscer \(13\), which is not present in any of the existing workload generators to the best of our knowledge.

Broadly speaking, caching algorithms such as LRU-k \(10\), MRU \(33\), etc. that track the recency of access are attempting to capture the current popularity distribution. Key-value stores designed for disk-based settings, such as Anna \(44\) and Faster \(32\) incorporate techniques to leverage the skew in popularity by moving hot data to memory. Recent work by Herodotou et al. \(37\) uses machine learning to automatically move data between different storage tiers in clusters. A recurring trend to note here is that the complexity of these existing schemes vary depending on the “budget” allowed by the setting, ranging from relatively simple LRU approach is used even in processor caches, to a more complex approach involving machine learning in large-scale clusters.

To this end, the budget available for learning in-the-loop with hash tables is extremely limited, as we see in our work (Fig. 6). In the seminal paper on learned indexes by Kraska et al. \(39\), the authors propose learning a hash function from the keys in the hash table such that collisions can be avoided altogether. However, recent work on learned hash functions \(43,5\) shows that this approach hits the wall due to two main reasons – cache sensitivity, and model complexity. While larger models are necessary to accurately capture arbitrary key distributions, the computation times become prohibitively high (50z higher \(43\)) due to increased cache misses from accessing the model parameters. The high cache sensitivity and low latency requirements of hash tables preclude the use of costly ML techniques for learning.

A noteworthy aspect of the VIP hashing method is that learning is performed online, i.e., the hash table does not pause operation at any time. In contrast, recent work \(36,43\) involves learning from the data offline before populating the hash table. Adapting to changing key distributions remains a challenge with these approaches, with the fallback being reverting to the default hash table implementation \(36\) or relearning \(39,43\), both of which require costly rehashing that pauses execution.

8. CONCLUSIONS & FUTURE WORK

Hashing is a low-latency operation that runs a tight loop of operations, and is sensitive to the effects of caching. Increasing the memory and computation footprint even by a small proportion can have a significant impact on performance as we see in \([5,1]\). Given these constraints, learning in-the-loop precludes the use of costly techniques and makes it necessary to use lightweight schemes while controlling the overhead as much as possible.

Overall, VIP hashing is comprised of four mechanisms – learning, adapting, sensing, and dynamically switching-on/off learning. These mechanisms \([42]\) along with our choice of parameters \([5,3]\) keep the overhead of learning in check compared to the gains. We evaluate VIP hashing using an extensive set of workloads (Fig. 6) that demonstrate the ability to learn on the fly in the presence of insert and delete operations, and shifting distributions. Our experiments involving PK-FK hash joins show that VIP hashing reduces the end-to-end execution time by 22%, while the gain in performance for point queries ranges from 3%-77% under medium skew. While the performance gain depends on the a host of factors (level of skew, proportion of insert and delete, etc.), the distinguishing property of VIP hashing is the ability to learn in a non-blocking, online fashion.

Broadly speaking, our work highlights the challenges of learning with cache sensitive, low latency data structures. While the major source of performance gain for VIP hashing has been from improvement in cache locality, the sensitivity of hash tables to effects of caching make learning very challenging \([5,1,43]\). Possible future work could involve studying other low latency data structures such as bloom filters \(29\), to see how cache locality can be improved by adapting to the data. Learning tasks involving such cache sensitive data structures will necessitate controlling the overhead, perhaps by using our approach of budgeted learning and non-intrusive sensing.

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### APPENDIX

## A. PROOF OF THEOREM 1

Theorem 1 (45.5.2) states that given keys $K_1, K_2, \ldots, K_n$ in a bucket with probability $p_1 > p_2 > \ldots > p_n$, such that the keys are in a random order initially. Then by applying Algorithm [1] the keys will converge to the sorted order of popularity as the number of fetch requests $N \to \infty$. We first make the following observation:

**Lemma 1.** Given two keys $K_1$ and $K_2$ with popularity $p$ and $(1 - p)$ respectively. Let $p > 0.5$. Given $N$ successful fetch requests are made, and keys $K_1$ and $K_2$ receive $N_1$ and $N_2$ requests respectively. Then,

$$\lim_{N \to \infty} \frac{N_1 - N_2}{N} = (2 \cdot p - 1) > 0$$

**Proof:**
B. INTRODUCING SKEW IN TPC-H

Fig. 15 shows the PK-FK (primary key-foreign key) constraints in TPC-H schema. Skew can arise in PK-FK relations when a some primary keys occur more frequently than others in the fact (FK) relation, i.e., the distribution of the FK attribute is skewed. Note that primary keys are unique, and thus by definition, skew cannot arise in the PK attribute. We considered the existing constraints in TPC-H schema (Fig. 15), and introduced skew in the FK attribute wherever possible. Table 4 details our findings – we have introduced skew in 5 out of 8 FK attributes, and we also describe the reasons for cases where skew could not be introduced. Wherever applicable, the level of skew can be adjusted by configuring the zipfian coefficient.

Table 4: Introducing skew in TPC-H relations. We introduce skew in the FK attribute wherever possible under existing constraints. For 5 out of 8 cases where skew was introduced, the level of skew can be configured through the zipfian coefficient.

The above lemma follows from the frequentist definition of probability. Thus, as \( N \to \infty \), we can be sure that more popular keys will receive more requests. This will hold pairwise for all the keys \( K_1, K_2, \ldots, K_n \) in the bucket chain, which motivates the following claim.

**Lemma 2.** Let \( \{ K_i \} \) be keys in a bucket with probability \( \{ p_i \}, i \in [N] \). Let \( K_1 \) be the most popular key in the bucket, i.e., \( p_1 > p_j \forall j \in [2, \ldots, N] \). Let the initial order of keys be random. Then, by running Algorithm 1, \( K_1 \) will be at the front of the chain as number of fetch requests \( N \to \infty \).

**Proof.** Suppose \( K_1 \) is at displacement \( d > 1 \). Let there be keys \( K_1, \ldots, K_{d-1} \) in front of \( K_1 \). Let the keys have received requests \( n_1, \ldots, n_{d-1} \). Let \( K_1 \) have received \( n \) requests. From Lemma 2, we know that

\[
\lim_{N \to \infty} n > n_i, \forall i \in [(d - 1)]
\]

Thus, \( K_1 \) would have received more requests than all the keys in front of it as \( N \to \infty \). From Algorithm 1, on the last request that \( K_1 \) received, it should have been swapped with a key with lower number of requests ahead of it. This contradicts our assumption that \( K_1 \) is at position \( d > 1 \).

Thus, the most popular key in the chain will be in the front as number of requests approaches infinity. By recursively applying Lemma 3 to the remaining keys in the bucket, we can prove that the keys will be in the sorted order of popularity as \( N \to \infty \).