Adaptive Precision Setting for Cached Approximate Values*

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Abstract

Caching approximate values instead of exact values presents an opportunity for performance gains in exchange for decreased precision. To maximize the performance improvement, cached approximations must be of appropriate precision: approximations that are too precise easily become invalid, requiring frequent refreshing, while overly imprecise approximations are likely to be useless to applications, which must then bypass the cache. We present a parameterized algorithm for adjusting the precision of cached approximations adaptively to achieve the best performance as data values, precision requirements, or workload vary. We consider interval approximations to numeric values but our ideas can be extended to other kinds of data and approximations. Our algorithm strictly generalizes previous adaptive caching algorithms for exact copies: we can set parameters to require that all approximations be exact, in which case our algorithm dynamically chooses whether or not to cache each data value.

We have implemented our algorithm and tested it on synthetic and real-world data. A number of experimental results are reported, showing the effectiveness of our algorithm at maximizing performance, and also showing that in the special case of exact caching our algorithm performs as well as previous algorithms. In cases where bounded imprecision is acceptable, our algorithm easily outperforms previous algorithms for exact caching.

1 Introduction

Adaptive data caching, e.g., [FC92, WJH97], plays a critical role in the performance of distributed information systems (such as the World-Wide Web) by adjusting the caching strategy dynamically as conditions change. Caching *approximate values* instead of exact values presents an opportunity for further performance gains in exchange for decreased precision, *e.g.,* [ABGMA88, BGM92, BP93, HSW94, KKO+98, OW00, PL90, WXCJ98]. However, naively choosing what appear to be good approximate values can result in performance gains that are a factor of two (or more) less than the gains achievable when approximate values are chosen carefully, without any improvement in precision. This paper focuses on the problem of setting the precision of cached approximate values dynamically and adaptively to achieve the best possible performance. Now let us motivate the problem somewhat formally, but still abstractly. More concrete details will be given in Section 2 and beyond.

1.1 Approximate Caching and Querying

An *approximate data caching environment* has one or more *data sources*, $S_1, \ldots S_n$. Each S_i hosts a set $\mathcal{V}_i$ of *exact data values*. Each exact value $V \in \mathcal{V}_i$ may be cached as an *approximation* by zero or more *caches* $C_1, C_2, \ldots C_m$, so each cache C_j may hold an approximation A_j to the exact value V. Whenever the value of V changes to V', source S_i applies a boolean test $Valid(A_j, V')$ for each approximation A_j cached by a C_j, to decide whether A_j is still a valid approximation for the new value V'. If $Valid(A_j, V')$ evaluates to $false$, the source creates a new approximation A'_j of V' and transmits it to C_j (a *value-initiated refresh*). Under this protocol, caches are guaranteed to always contain valid approximations, modulo communication overhead.

Typically, not all valid approximations have the same *precision*, which we will represent by a nonnegative value $Prec(A_j)$. At one extreme, an approximation A_j of V having $Prec(A_j) = \infty$ is an exact copy of V. At the other extreme, if $Prec(A_j) = 0$, then A_j contains no information about V. In general, an exact value can be approximated with varying degrees of precision between 0 and ∞. For example, an integer value could be approximated by an interval, with validity requiring the interval to contain the exact value, and with the width of the interval determining the (inverse of) the precision.

Cached approximate values are accessed by *queries* running at a cache. If a query finds the precision offered by an approximate value A_j to be insufficient, the query may request the exact value V from the remote source S_i. The source responds with the current exact value V as well as a new approximation A'_j to be used by subsequent queries. This exchange is called a *query-initiated refresh*.

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1.2 Maximizing Performance

Let us assume that our goal is to minimize overall network traffic. Then, in an approximate data caching environment as described in Section 1.1, we want to avoid both value- and query-initiated refreshes as much as possible. The likelihood that either type of refresh will occur depends on the precision of the cached approximation. On one hand, value-initiated refreshes are less likely to occur if the precision is low, since low-precision approximations are likely to remain valid even when the exact value fluctuates to some degree. On the other hand, query-initiated refreshes are less likely to occur if the precision is high, since queries are more likely to find the precision sufficient and not request the exact value from the source. Although the likelihood of each type of refresh can be controlled by adjusting the precision, decreasing the likelihood of one type of refresh increases the likelihood of the other. Therefore, it is not obvious how best to set the precision of cached approximations so as to minimize the overall cost incurred by refreshes of both types.

We will present a parameterized algorithm for adjusting the precision of cached approximations adaptively to achieve the best performance as data values, precision requirements, and/or overall workload vary. The specific problem we address considers interval approximations to numeric values, but our ideas can be extended to other kinds of data and approximations, as discussed briefly in Sections 2.1 and 5. Our algorithm adjusts the precision of each cached approximation independently, and it strictly generalizes previous adaptive caching algorithms for exact copies (*e.g.*, [WJH97]): we can set parameters to require that all approximations be exact, in which case our algorithm dynamically chooses whether or not to cache each data value. We have implemented our algorithm and performed tests over synthetic and real-world data. We report a number of experimental results, which show the effectiveness of our algorithm at maximizing performance, and also show that in the special case of exact caching our algorithm performs as well as previous algorithms. In cases where it is acceptable for queries to produce answers with bounded imprecision, our algorithm easily outperforms previous algorithms for exact caching.

1.3 Related Work

The previous work most similar to ours is *Divergence Caching* [HSW94], which also considers the problem of setting the precision of approximate values in a caching environment. In their setting, precision is based on number of updates to source values and not on the values themselves—the precision of a cached approximation is inversely proportional to the number of updates since the last cache refresh (referred to as a *stale value approximation*). The Divergence Caching algorithm proposed in [HSW94] works well in their environment, but does not generalize easily to the kinds of approximations we consider, which are based on the magnitude of source updates instead of their frequency. A more thorough comparison is given in Section 4.7, where we discuss the differences between our work and Divergence Caching in more detail, and show performance results indicating that our approach modestly outperforms Divergence Caching when we specialize ours to the stale value approximations of [HSW94].

No other work that we know of addresses precision setting of cached approximate values while subsuming exact caching techniques. The work on caching approximate values in *Interval Relations* [BP93], *TRAPP* [OW00], *Epsilon Serializability* [PL90], and *TACT* [YV00] does not focus on the problem of how to set precision optimally. In *Quasi-Copies* [ABGMA88] and the *Demarcation Protocol* [BGM92], precision cannot be adjusted dynamically. Work on *Moving Objects Databases* [WCD+98] considers setting precision of cached approximations, but queries are not permitted to request exact values from sources so remote read costs are not taken into account. Conversely, in *Soft Caching* [KKO+98], updates to the exact source value are not considered, so value-initiated refreshes are not considered when setting precision.

1.4 Outline of Paper

The remainder of the paper is structured as follows. In Section 2 we introduce the numeric data values and approximations we consider, and we describe our adaptive precision-setting algorithm. We justify our algorithm mathematically in Section 3. In Section 4 we describe our simulation environment and test data sets, then present our performance results. We first justify empirically our claim from Section 3 that our algorithm converges to optimal performance, by considering steady-state synthetic data. We then switch to real-world data, finding the best parameter settings to maximize the performance of our algorithm under dynamically changing conditions. Next we demonstrate that our algorithm performs as well as previous algorithms in the special case of exact caching, and outperforms exact caching algorithms when exact precision is not required. Finally, we compare our algorithm against Divergence Caching. In Section 5 we conclude and discuss avenues for future work.

2 Setting Interval Precision Adaptively

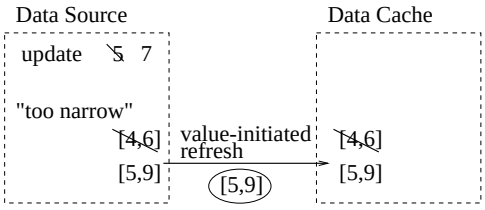
In this section we describe our algorithm for setting the precision of *interval approximations* to numeric values. Our ideas can be extended to other types of data and approximations, as discussed briefly at the end of this section. An interval approximation $[L, H]$ is a valid approximation (recall Section 1.1) of a numeric value V, *i.e.*, $Valid([L, H], V)$, if V lies in the interval, *i.e.*, $L \leq V \leq H$. The precision is the reciprocal of the width of the interval: $Prec([L, H]) = \frac{1}{H-L}$. At one extreme, a zero-width interval contains only the exact value and thus has infinite precision. In the other extreme, an interval of infinite width gives no information about the exact value and thus has zero precision. We assume that intervals remain

constant until a refresh occurs. Although intervals that vary as a function of time are more general, we have found empirically that they are not particularly helpful, as discussed in Section 4.5.

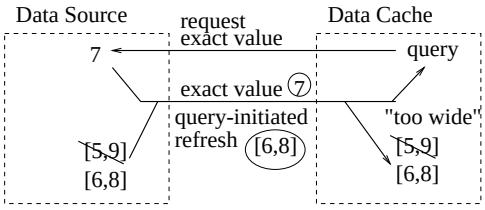
Whenever the precision $Prec([L, H])$ of a cached interval is not adequate for a query running at the cache, *i.e.*, the interval is too wide, the query initiates a refresh by requesting the exact value from the source. (For examples of the kinds of queries that would run over approximate cached values with precision requirements, see, *e.g.*, [OW00, FMP+00].) The source responds with the current exact value as well as a new interval $[L', H']$ to be used by subsequent queries. The cost incurred during a query-initiated refresh will be denoted C_{qr}. A value-initiated refresh incurs cost C_{vr}, and occurs whenever the exact value V at a data source exceeds its interval $[L, H]$ in some cache, causing $Valid([L, H], V)$ to become $false$. Notice that value-initiated refreshes are never required for intervals of infinite width ($H - L = \infty$). Conversely, when an interval has zero width ($H - L = 0$), then a value-initiated refresh occurs every time V changes.

Both types of refreshes (value- and query-initiated) provide an opportunity for the source to adjust the interval being cached. For now let us assume that whenever the source provides a new interval to the cache, the interval is centered around the current exact value. (Uncentered intervals are considered in Section 4.5, and like time-varying intervals they usually turn out not to be helpful.) Therefore, an approximation for a value V is uniquely determined by the interval width W. The objective in selecting a good interval width is to avoid the need for future refreshes, since we want to minimize communication cost. To avoid value-initiated refreshes, the interval should be wide enough to make it unlikely that modifications to the exact value will exceed the interval. On the other hand, to avoid query-initiated refreshes, the interval should be as narrow as possible. As discussed in Section 1.2, since decreasing the chance of one type of refresh increases the chance of the other, it is not obvious how best to choose an interval width that minimizes the total probability that a refresh will be required.

Both of the factors that affect the choice of interval width—the variation of data values (which causes value-initiated refreshes) and the precision requirements of user queries (which cause query-initiated refreshes)—are difficult to predict, so we propose an adaptive algorithm that adjusts the width W as conditions change. The overall strategy is as follows. First start with some value for W. Each time a value-initiated refresh occurs (a signal that the interval was too narrow), increase W when sending the new interval. Conversely, each time a query-initiated refresh occurs (a signal that the interval was too wide), decrease W. This strategy, illustrated in Figure 1, finds a middle ground between very wide intervals that the value never exceeds yet are exceedingly imprecise, and very narrow intervals that are precise but need to be refreshed constantly as the value fluctuates.



(a) Growing the interval on a value-initiated refresh



(b) Shrinking the interval on a query-initiated refresh

Figure 1: Adaptive precision-setting algorithm.

We now define our algorithm precisely. The algorithm relies on five parameters as follows. The first two are functions of the particular distributed caching environment, while the remaining three can be set to tune the algorithm.

(1) the value-initiated refresh cost C_{vr}
(2) the query-initiated refresh cost C_{qr}
(3) the *adaptivity parameter* $\alpha \geq 0$
(4) the *lower threshold* $\tau_0 \geq 0$
(5) the *upper threshold* $\tau_\infty \geq 0$

These parameters and others we will introduce later are summarized in Table 1. Let us define a *cost factor* ρ as $\rho = 2 \cdot \frac{C_{vr}}{C_{qr}}$. The cost factor is based on the ratio of the two refresh costs and is used to determine how often to grow and shrink the interval width W as refreshes occur. The mathematical justification for multiplying the ratio by 2 is given in Section 3.

Our algorithm sets the new width W' for a refreshed interval based on the old width W during each value- or query-initiated refresh as follows. Recall that $\alpha \geq 0$ is the adaptivity parameter.

- value-initiated refresh:
  with probability $\min\{\rho, 1\}$, set $W' \leftarrow W \cdot (1 + \alpha)$
- query-initiated refresh:
  with probability $\min\{\frac{1}{\rho}, 1\}$, set $W' \leftarrow \frac{W}{(1+\alpha)}$

In Section 3 we will justify mathematically why these are the optimal probability settings for width adjustment. Intuitively, the idea is to continually adapt the interval width to balance the likelihood of the two types of refreshes. However, if two value-initiated refreshes are more expensive than one query-initiated refresh, *i.e.*, $\rho > 1$, a larger width is preferred, so the width is not decreased on every query-initiated refresh. Conversely, if one query-initiated refresh is more expensive than two value-initiated refreshes, *i.e.*, $\rho < 1$, a smaller width

Symbol	*Meaning*	*Note*
C_{vr}	cost of a value-initiated refresh	used to determine cost factor ρ
C_{qr}	cost of a query-initiated refresh	used to determine cost factor ρ
ρ	cost factor defined as $2 \cdot \frac{C_{vr}}{C_{qr}}$	determines width adjustment probability
Ω	cost rate (per time step)	metric our algorithm minimizes
W	width of a cached approximation	set adaptively by our algorithm
W^*	width that minimizes the cost rate Ω	our algorithm converges to $W = W^*$
α	adaptivity parameter	how much to adjust width
τ_0	lower threshold	widths below τ_0 are set to 0
τ_∞	upper threshold	widths above τ_∞ are set to ∞
P_{vr}	probability of a value-initiated refresh	increases with precision
P_{qr}	probability of a query-initiated refresh	decreases with precision
δ	precision constraint of a query	parameter to experiments
δ_{avg}	average precision constraint of queries	parameter to experiments
$\Delta\delta$	variation of precision constraints across queries	parameter to experiments
δ_{min}	minimum precision constraint	derived from δ_{avg} and $\Delta\delta$
δ_{max}	maximum precision constraint	derived from δ_{avg} and $\Delta\delta$
n	number of data sources	parameter to experiments
κ	cache size (in number of approximate values)	parameter to experiments
T_q	time period between queries	parameter to experiments
s	random walk step size	used for analysis in Appendix A

Table 1: Model and algorithm symbols.

is preferred, so the width is not increased on every value-initiated refresh. Whenever the width is adjusted, the magnitude of the adjustment is controlled by the adaptivity parameter α.

Now let us consider the lower and upper thresholds, τ_0 and τ_∞. When our algorithm computes an interval width $W < \tau_0$, we instead set $W = 0$, and when we compute a $W \geq \tau_\infty$, we instead set $W = \infty$. The purpose of these thresholds is to accommodate boundary cases where either exact caching ($W = 0$) or no caching ($W = \infty$) is appropriate, since without this mechanism the width would never actually reach these extreme values. The source still retains the original width, and uses it when setting the next width W'. As part of our performance study we describe how to set these parameters and others.

If a cache does not have enough space to store an approximation for every data value requested, it evicts the widest intervals, since they are the least precise approximations and thus contribute least to overall cache precision. (This decision also is based on original widths, not on 0 or ∞ widths due to thresholds.) Caches do not need to notify sources when approximations are evicted. If an evicted approximation incurs a value- or query-initiated refresh, the modified approximation may be cached and another evicted, or the modified approximation may still be the widest and remain uncached.

2.1 Other Types of Data and Approximations

We have presented our algorithm specifically for interval approximations to numeric source values, but other types of source data and approximations can use a similar numeric approach. For example, non-numeric data can be approximated by stale versions, where precision is quantified as a numeric measure of the deviation between the exact value and the cached approximation. Then our algorithm can be used to set maximum deviations adaptively in order to optimize overall performance. In Section 4.7 we apply our algorithm in this fashion to emulate Divergence Caching [HSW94], where the deviation metric is the number of updates to the exact value not reflected in the cached approximation. Further exploration of this general topic is left as future work.

3 Justification of Algorithm

In this section we justify our algorithm mathematically. Let P_{vr} and P_{qr} represent the probability that a value- or query-initiated refresh (respectively) will occur at each time step. Then the expected *cost rate* per time step $\Omega = C_{vr} \cdot P_{vr} + C_{qr} \cdot P_{qr}$, where C_{vr} and C_{qr} are the costs of value- and query-initiated refreshes (respectively) as introduced in Section 2.

For a given cached approximation with width W, the probability of each type of refresh can be written as $P_{vr} = \frac{K_1}{W^2}$ and $P_{qr} = K_2 \cdot W$, where K_1 and K_2 are *model parameters* that depend on the nature of the data and updates, the frequency of queries, and the distribution of query precision requirements. In Appendix A we justify these equations in detail for the case of interval approximations. However, the important—and intuitive—point is that, for all kinds of data

and approximations, the value-initiated refresh probability increases with precision (*i.e.*, with a smaller W), while the query-initiated refresh probability decreases with precision.

Now that we know how P_{vr} and P_{qr} depend on W, we can rewrite our cost rate Ω in terms of W: $\Omega(W) = C_{vr} \cdot \frac{K_1}{W^2} + C_{qr} \cdot K_2 \cdot W$. Our goal then is to find the value for W that minimizes this expression, which is achieved by finding the root of the derivative. Using this approach, the optimal value for W is $W^* = (2 \cdot \frac{C_{vr}}{C_{qr}} \cdot \frac{K_1}{K_2})^{(\frac{1}{3})} = (\rho \cdot \frac{K_1}{K_2})^{(\frac{1}{3})}$, where $\rho = 2 \cdot \frac{C_{vr}}{C_{qr}}$ is the cost factor we defined in Section 2. Unfortunately, setting the interval width W based on this formula for W^* is difficult unless update behaviors and query/update workloads are stable and known in advance, since model parameters K_1 and K_2 depend on these factors. One approach is to monitor these factors at run-time to set K_1 and K_2 appropriately, which is similar to the approach taken by Divergence Caching [HSW94]. However, we will see that our approach achieves the same optimal interval width W^* without the monitoring complexity or overhead.

Our approach is motivated by the observation that $\rho \cdot P_{vr} = P_{qr}$ when $W = W^* = (\rho \cdot \frac{K_1}{K_2})^{(\frac{1}{3})}$. Let us first consider the special case where $\rho = 1$. (We will discuss other values for ρ momentarily.) In this special case, the optimal value for W occurs exactly when the two types of refreshes are equally likely. Our algorithm takes advantage of this observation by dynamically adjusting the interval width W so as to equate the likelihood of each type of refresh, thereby discovering the optimal width W^*. Our algorithm adjusts the width W based solely on observing refreshes as they occur, without the need for storing history or for direct measurements of updates, queries, or precision requirements. Furthermore, as conditions change over time, our algorithm adapts to always move W toward the optimal width W^*. The *adaptivity parameter* $\alpha \geq 0$, introduced in Section 2, controls how quickly the algorithm is able to adapt to changing conditions.

The graph in Figure 2 illustrates the principle behind our algorithm. Still considering $\rho = 1$, it plots the cost rate Ω and refresh probabilities P_{vr} and P_{qr} as functions of the interval width W. The model parameters K_1 and K_2 are fixed as $K_1 = 1$ and $K_2 = \frac{1}{200}$. (These values were set based roughly on a query period of 10 seconds and an average precision constraint of 10. Changing these values only shifts the graph.) Notice that the width W^* that minimizes the cost rate Ω corresponds exactly to the point where the curves for P_{vr} and P_{qr} cross. Therefore, by equalizing the chance that refreshes will be either value- or query-initiated, the optimal width W^* is discovered.

Now consider the general case where ρ can have any value. Our algorithm still discovers the optimal width W^*. Recall that the optimal width occurs when $\rho \cdot P_{vr} = P_{qr}$. Our algorithm achieves this condition by not always adjusting the interval width on every refresh. In cases where $\rho < 1$, it is desirable for value-initiated refreshes to be more likely than query-initiated refreshes. Thus, the width is decreased on every query-initiated refresh but only increased with probability ρ on value-initiated refreshes. Conversely, in cases where $\rho > 1$, the width is increased on every value-initiated refresh but only decreased with probability $\frac{1}{\rho}$ on query-initiated refreshes.

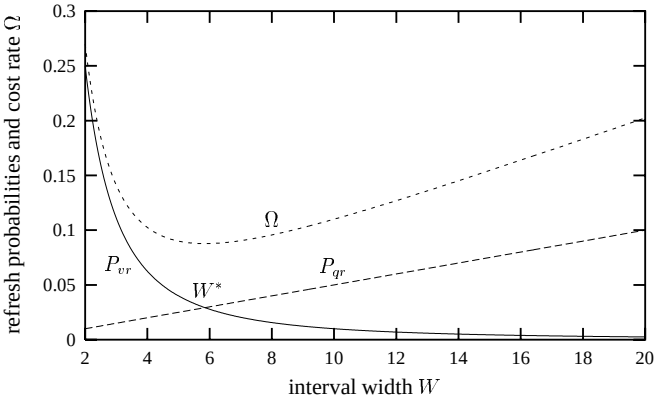


Figure 2: Cost rate and refresh probabilities when $\rho = 1$ as functions of interval width.

4 Performance Study

In this section we present the results of a performance study of our algorithms, and of related algorithms, using synthetic data as well as real-world data taken from a network monitoring application. We first describe our simulation environment in Section 4.1. In Section 4.2 we present results demonstrating empirically that our algorithm does achieve optimal performance in the steady state, as motivated mathematically in Section 3. We introduce our real-world data set in Section 4.3, and in Section 4.4 we present results indicating how best to set the tunable parameters of our algorithm. In Section 4.5 we discuss some variations of our algorithm that proved to be unsuccessful in most cases. In Section 4.6 we show that our algorithm precisely matches the performance of adaptive exact caching when exact precision is required, and outperforms exact caching when exact precision is not required. Finally, in Section 4.7 we discuss how our algorithm can be applied in the Divergence Caching [HSW94] setting, and we empirically compare the two approaches.

4.1 Simulator Description

To study our adaptive algorithm empirically, we built a discrete event simulator of an environment with n data sources and one cache. Each source holds one exact numeric value, and the cache can hold up to $\kappa \leq n$ interval approximations to exact source values. In our synthetic experiments, exact values are updated every time unit (which we set to be one second) with a specified update distribution. In our real-world experiments, the timing and values of updates are generated from the network performance data we are using. For both types of experiments, a query is executed at the cache every

T_q seconds. We will describe how queries and query precision requirements are generated momentarily, but it is important to note that our algorithm is not specialized to any particular type of query. The only assumption made by our algorithm is that for each approximate value, the probability of a query-initiated refresh is proportional to the width of the approximation.

The queries we generate attempt to balance generality and practicality and are inspired by the "bounded aggregate" queries in [OW00]. Each query asks for either the SUM or MAX of a set of approximate values in the cache, where the query result is itself an interval approximation. Each query is accompanied by a *precision constraint* $\delta \geq 0$ specifying the maximum acceptable width of the result.[1] Precision constraints are generated based on parameters δ_{avg} (average precision constraint) and $\Delta\delta$ (precision constraint variation): they are sampled from a uniform distribution between $\delta_{min} = \delta_{avg} \cdot (1 - \Delta\delta)$ and $\delta_{max} = \delta_{avg} \cdot (1 + \Delta\delta)$. Using the algorithms in [OW00], from the query type, precision constraint, and approximate data, a (possibly empty) subset of the approximations are selected for query-initiated refresh, after which the desired precision for the query result is guaranteed. Again, it is important to note that our algorithm is not aware of or tuned to these query types or this method of expressing precision requirements—they are used solely to generate a realistic and interesting query load.

4.2 Optimality of Algorithm

Our first experiment was a simple one to verify the correctness of our basic model and the optimality of our algorithm on steady-state data. We used synthetic data consisting of only one source data item, whose value performs a random walk in one dimension: every second, the value either increases or decreases by an amount sampled uniformly from $[0.5, 1.5]$. We simulated a workload having query period $T_q = 2$ seconds, average precision constraint $\delta_{avg} = 20$, and precision constraint variation $\Delta\delta = 1$, in an environment with $\rho = 1$. The query type (SUM or MAX) is irrelevant since we have only one data item.

Our goal was to establish the correctness of our model for the refresh probabilities P_{vr} and P_{qr}, *i.e.*, to show that as the data undergoes a random walk P_{vr} and P_{qr} are proportional to $\frac{1}{W^2}$ and W respectively, and for $\rho = 1$, equalizing P_{vr} and P_{qr} maximizes performance. Thus, we fixed interval width W for each run (*i.e.*, we turned off the part of our algorithm that adjusts widths dynamically), but varied W across runs. We measured the average rate at which value- and query-initiated refreshes occurred, taking their reciprocals to obtain P_{vr} and P_{qr}, respectively. Measurements taken during an initial warm-up period were discarded, as in all subsequent reported experiments.

[1] Note that queries specify absolute precision constraints and not relative ones, which would factor in the magnitude of the result. Converting relative precision constraints to absolute ones is discussed in [OW00, YV00], but full treatment of relative precision constraints is a topic of future work.

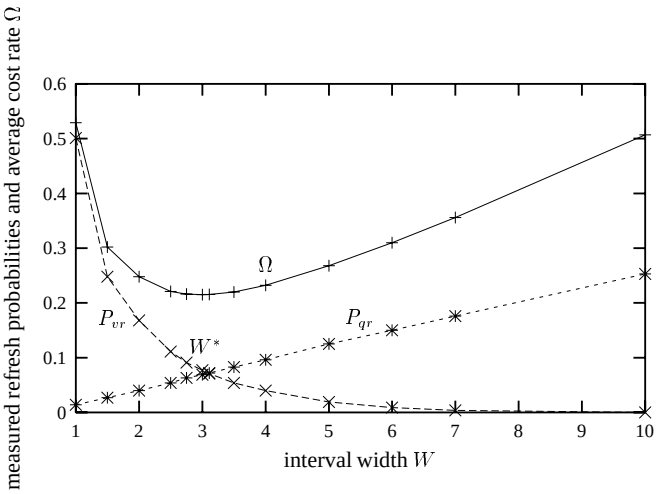


Figure 3: Measured cost rate and refresh probabilities when $\rho = 1$ as functions of interval width.

The results are shown in Figure 3, which bears a striking resemblance to Figure 2. The measured values for P_{vr} and P_{qr} are indeed proportional to $\frac{1}{W^2}$ and W, respectively, and the measured cost rate Ω for different values of W also is shown in Figure 3. From this graph we verify empirically that, in the $\rho = 1$ case, the minimum cost rate does indeed occur when the two refresh probabilities are equal.

We then ran the same experiment letting our algorithm adjust interval widths. The algorithm converged to $W = 3.11$, resulting in performance within 1% of the optimal W^* shown in Figure 3. We further evaluated the optimality of our algorithm with all combinations of $T_q \in \{1, 2\}$, $\delta_{avg} \in \{10, 20\}$, and $\rho \in \{1, 4\}$. In all of these scenarios, our algorithm converged to a width resulting in performance within 5% of optimal.

4.3 Our Algorithm in a Dynamic Environment

To test our adaptive algorithm under real-world dynamic conditions, we used publicly available traces of network traffic levels between hosts distributed over a wide area during a two hour period [PF95]. For each host, the data values we use represent a one minute moving window average of network traffic every second, and we picked the 50 most heavily trafficked hosts as our simulated data sources. Traffic levels at these hosts ranged from 0 to $5.2 \cdot 10^6$ bytes per second. The simulated cache keeps an approximation of the traffic level for at most κ of the $n = 50$ sources, where κ is a parameter of the algorithm that is set to $\kappa = 50$ unless otherwise stated. Queries are executed at the cache every T_q seconds, computing either the MAX or SUM of traffic over 10 randomly selected sources. In all of our experiments, measurements of the overall cost per unit time Ω were taken after an initial warm-up period.

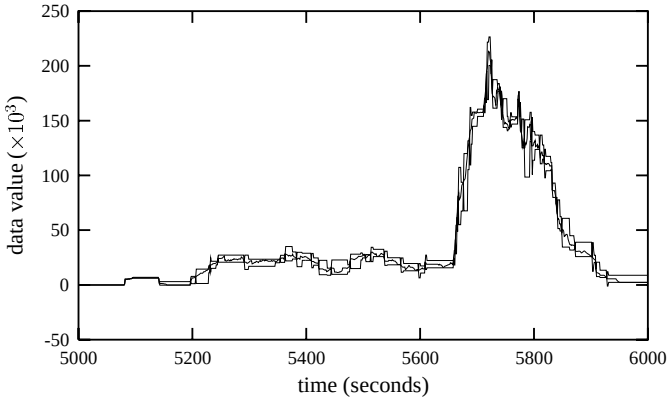


Figure 4: Source value and cached interval over time for small precision constraints.

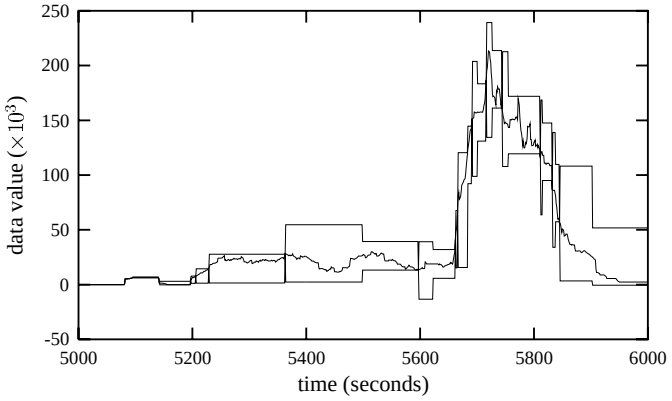


Figure 5: Source value and cached interval over time for large precision constraints.

In our experiments, we consider refresh costs C_{vr} and C_{qr} that are intended to model network behavior under common consistency models and concurrency control schemes, although our algorithm handles arbitrary cost values. Usually, performing a remote read requires one request message and one response message, so $C_{qr} = 2$. If two-phase locking is used for cache consistency, then $C_{vr} = 4$ since two round-trips are required and thus $\rho = 2 \cdot \frac{4}{2} = 4$. Otherwise, if updates are simply sent to the cache, *e.g.,* in a multiversion or loosely consistent concurrency control scheme, then $C_{vr} = 1$ and $\rho = 2 \cdot \frac{1}{2} = 1$. Thus, most of our experiments consider the $\rho \in \{1, 4\}$ cases.

Figures 4 and 5 depict the exact value at one of the data sources for a short segment of a run, along with the cached interval approximation as the value and interval change over time. For illustrative purposes we selected a portion of the run where a host became active after a period of inactivity. These figures illustrate the interval widths selected by our adaptive algorithm with parameters $\alpha = 1$, $\tau_0 = 0$, and $\tau_\infty = \infty$, when SUM queries are executed every second (*i.e.,* $T_q = 1$) and $\rho = 1$. Figure 4 uses average precision constraint $\delta_{avg} = 50K$, while Figure 5 uses average precision constraint $\delta_{avg} = 500K$.[2] When the average precision constraint is small, as in Figure 4, narrow intervals are favored. (To satisfy the precision constraints of SUM queries, the width of each of the 10 individual intervals being summed should be on the order of $\frac{\delta_{avg}}{10} = \frac{50K}{10} = 5K$ [OW00].) When the average precision constraint is large, as in Figure 5, wide intervals (on the order of $\frac{\delta_{avg}}{10} = \frac{500K}{10} = 50K$) are favored.

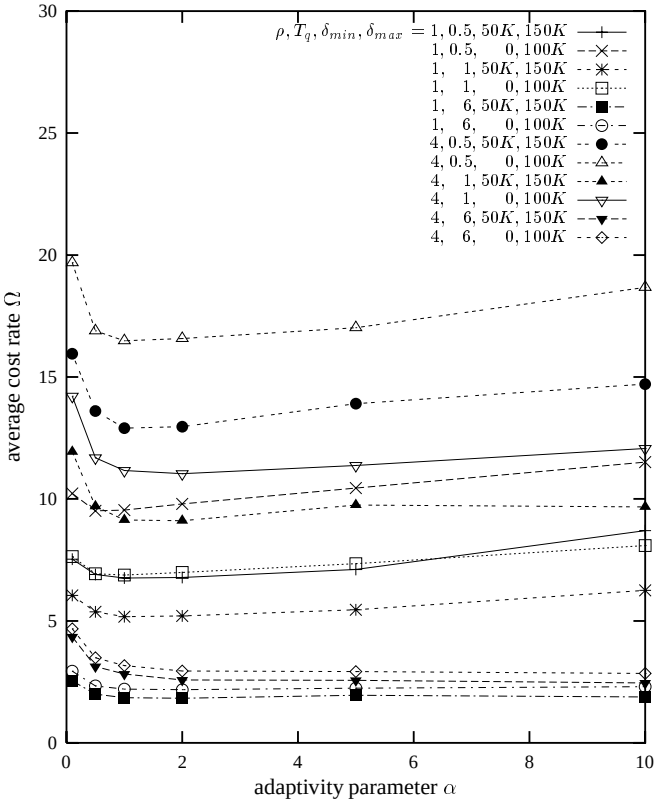


Figure 6: Effect of varying the adaptivity parameter α.

4.4 Setting Parameters

Next, we describe our experiments whose goal was to determine good values for the adaptivity parameter α and the lower and upper thresholds τ_0 and τ_∞. First, fixing $\tau_0 = 0$ and $\tau_\infty = \infty$ (meaning we never reset bound widths based on thresholds), we studied the effect of the adaptivity parameter α on performance. Figure 6 shows the results. We used SUM queries and varied α, considering several different settings for T_q, δ_{min}, δ_{max}, and ρ. In this and subsequent experiments, the y-axis cost rate Ω is the average for the entire run. All combinations of $T_q \in \{0.5, 1, 6\}$, $(\delta_{min}, \delta_{max}) \in \{(50K, 150K), (0, 100K)\}$, and $\rho \in \{1, 4\}$ are shown. From these experiments and similar experiments using MAX queries, we determined that a good overall set-

[2] In the remainder of this section we abuse the abbreviation K for $\times 10^3$.

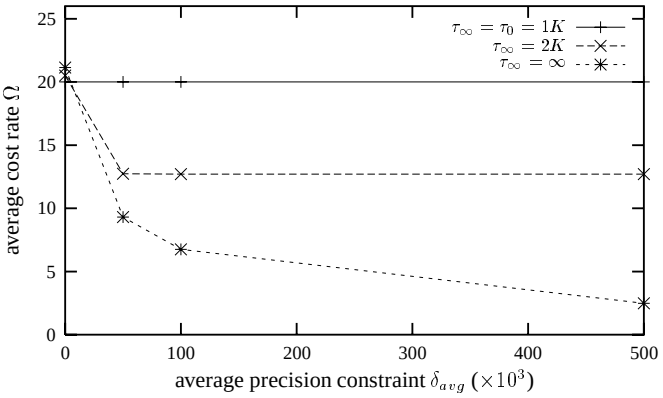


Figure 7: Performance of settings for τ_∞, query period $T_q = 0.5$.

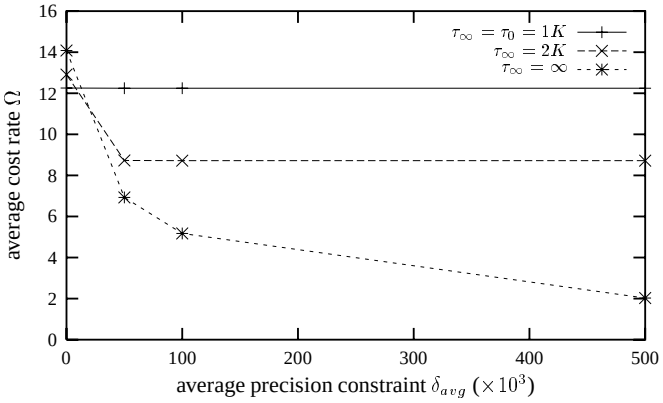


Figure 8: Performance of settings for τ_∞, query period $T_q = 1$.

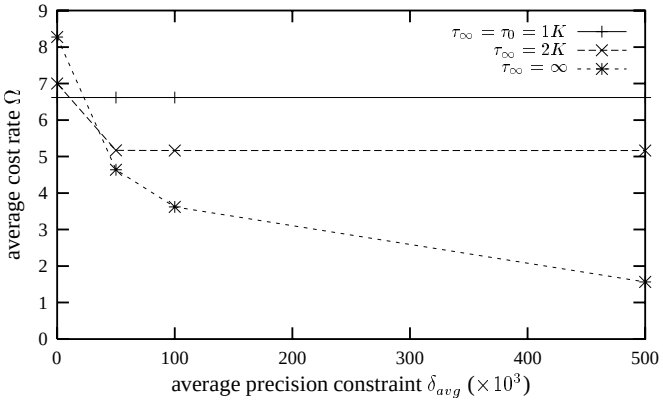


Figure 9: Performance of settings for τ_∞, query period $T_q = 2$.

ting for α is 1. Recall from Section 2 that using $\alpha = 1$, the width W is doubled on value-initiated refreshes and halved on query-initiated refreshes.

We now address setting the lower threshold τ_0. Recall that the purpose of the lower threshold τ_0 is to force the interval width of an approximation to 0 when it becomes very small. A nonzero τ_0 parameter is necessary for queries that ask for exact answers, *i.e.*, have $\delta = 0$: with $\tau_0 = 0$, exact values would not be cached, so such queries would always require source refreshes. It turns out that the performance under a workload with $\delta_{avg} = 0$ is not very sensitive to the value of τ_0, as long as $\tau_0 > 0$. However, setting τ_0 too large can adversely affect queries with small, nonzero precision constraints, since nonzero intervals of width below τ_0 are not permitted. Therefore, to accommodate queries with a variety of precision constraints, τ_0 should be set to a small positive constant ϵ less than the smallest meaningful nonzero precision constraint. For our network data, differences in precision of $\epsilon = 1K$ are not very significant, so we set $\tau_0 = \epsilon = 1K$. This setting for τ_0 has only a small impact on queries even with moderately large precision constraints. For example, for precision constraints between $\delta_{min} = 5K$ and $\delta_{max} = 15K$, the performance degradation is less than 1% (for $T_q = 1$, $\tau_\infty = \infty$, and $\rho = 1$).

Having determined good values for α and τ_0, we now consider the upper threshold τ_∞. Setting τ_∞ to a small value improves performance for high-precision workloads since it eliminates caching of approximations that are not useful to queries. However, a small τ_∞ degrades the performance of low-precision workloads, *i.e.*, those having large precision constraints. To illustrate this tradeoff, in Figures 7, 8, and 9 we plot performance as a function of the average precision constraint δ_{avg}. Each graph corresponds to a different query period T_q and shows the performance using three different settings of τ_∞, holding all other parameters fixed: $\rho = 1$, $\Delta\delta = 0.5$, $\tau_0 = 1K$, and $\alpha = 1$. Workloads having $\delta_{avg} = 0$ perform best when $\tau_\infty = \tau_0$, which guarantees that all intervals are treated as having either no width ($W = 0$) or infinite width ($W = \infty$). That is, either the exact value is cached or effectively no value is cached at all. Since queries with $\delta = 0$ require exact precision, cached intervals that are not exact are of no use. Note that whenever we set $\tau_\infty = \tau_0$, performance is independent of δ_{avg} as illustrated by the horizontal lines in Figures 7, 8, and 9. For workloads having a range of different precision constraints, the upper threshold τ_∞ should be set to ∞.

Although these guidelines for setting the upper threshold τ_∞ apply to most types of queries including our SUM queries, there are exceptions. For example, values can be eliminated as candidates for the exact maximum based on intervals of finite, nonzero width [OW00]. Therefore, for MAX queries, approximate values can be useful to cache even when exact precision is required in all query answers. We have verified experimentally that for MAX queries, setting $\tau_\infty = \infty$ gives the best performance for all values of δ_{avg}, including $\delta_{avg} = 0$.

In summary, with parameter settings $\alpha = 1$, $\tau_0 = \epsilon$, and $\tau_\infty = \infty$, our algorithm adaptively selects intervals that

give the best possible performance under dynamically varying conditions. When $\Delta\delta = 0$, each query has the same precision constraint, so it is easier for the algorithm to discover the best precision for cached intervals. On the other hand, if $\Delta\delta$ is large, each query has a different precision constraint, making it harder to find interval widths that work well across multiple queries. Fortunately, it turns out that the degradation in performance due to a wide distribution of precision constraints is small. We verified that the performance of our algorithm is not very sensitive to the precision constraint distribution for several different average precision constraints, while holding the other parameters fixed: $T_q = 1$, $\tau_0 = 1K$, $\tau_\infty = \infty$, and $\rho = 1$. When $\delta_{avg} = 100K$, the difference in performance between a workload with $\Delta\delta = 0$ and $\Delta\delta = 1$ is only 1.9%. When $\delta_{avg} = 10K$, the difference is 5.5%. When $\delta_{avg} = 5K$, the difference is less than 1%.

4.5 Unsuccessful Variations

We experimented with a number of variations to our algorithm that seemed intuitive but proved unsuccessful in practice: using uncentered intervals, using intervals that vary as functions of time, and adjusting intervals based on the refresh history. We report briefly on our experience with each variation.

An interval is *uncentered* if, at refresh time, the interval does not bound the exact value symmetrically. Thus, two width values are maintained instead of one: an upper width and a lower width. The source independently adjusts the upper and lower widths as follows. Each time a value-initiated refresh occurs due to the value exceeding the upper bound, then with probability $\min\{\rho, 1\}$ the upper width is increased. Conversely, when the value drops below the lower bound, with the same probability the lower width is widened. Whenever a query-initiated refresh occurs, with probability $\min\{\frac{1}{\rho}, 1\}$ both widths are decreased. In our experiments with both our synthetic random walk data and our real-world network monitoring data, the uncentered strategy performed worse than the centered strategy. However, in the case of synthetic *biased* random walk data, where values were much more likely to go up than down, using uncentered intervals improved performance slightly over using centered intervals.

A second unsuccessful variation is to use approximations that become more approximate over time. In this paper our approximations are intervals $[L, H]$ whose endpoints are constant with respect to time. A more general approach is to make both L and H functions of time t. We ran experiments that showed that using intervals whose width increases with time proportionately to $t^{\frac{1}{2}}$ or $t^{\frac{1}{3}}$ resulted in worse performance than using constant intervals, both for the network monitoring data and unbiased synthetic random walk data. For biased random walk data (as described in the previous paragraph), the best interval functions turned out to be those having both endpoints increase linearly with time: $L(t) = k \cdot t$ and $H(t) = k \cdot t$, where the constant $k > 0$ is adjusted to match the average rate at which the data value increases. But, for general scenarios where the data does not predictably increase or decrease, constant intervals are preferred. Furthermore, constant intervals are much easier to index [KPS00] than intervals that are functions of time. Finally, time-varying intervals can be tricky to implement, especially when an upper bound decreases or a lower bound increases with time, since an approximation can become invalid based on time alone.

A third variation we tried is to have the algorithm consider the past r refreshes when deciding how to adjust the interval. In this variation, the width is increased if the majority of the r most recent refreshes were value-initiated. Otherwise, the width is decreased. We also experimented with various techniques to weight recent refreshes within r more heavily. However, none of these schemes outperformed the algorithm presented in this paper, which effectively sets $r = 1$ making it the most adaptive and simplest to implement.

4.6 Subsumption of Exact Caching

In this section we compare our algorithm against a state-of-the-art adaptive algorithm for deciding whether to cache exact replicas, which we derive from the replication algorithm in [WJH97]. In this algorithm, the number of requested reads r and writes w to each data value are counted. The caching strategy for every data value is reevaluated every x reads and/or writes to the value, *i.e.*, whenever $r + w \geq x$. At reevaluation, the projected cost of not caching, *i.e.*, the cost of performing r remote reads $\mathcal{C}_{nc} = r \cdot C_{qr}$ is computed. Similarly, the projected cost of caching, *i.e.*, the cost of performing w remote writes, $\mathcal{C}_c = w \cdot C_{vr}$ is computed. The value is cached if and only if $\mathcal{C}_c < \mathcal{C}_{nc}$. If the cache has limited space, values having the lowest cost difference $\mathcal{C}_{nc} - \mathcal{C}_c$ are evicted and the source is notified of the eviction. Under dynamic conditions, it has been shown that this adaptive exact caching strategy continually approaches the optimal strategy [WJH97].

Figures 10, 11, 12, and 13 compare our algorithm against the exact caching algorithm of [WJH97] for SUM queries executed every $T_q \in \{0.5, 1, 2, 5\}$ seconds. For each run, we first determined the best setting for parameter x in the exact caching algorithm. Thus we changed the value of x, which varied from 3 to 45, between runs, whereas all of our own parameters remained fixed: $\alpha = 1$, $\tau_0 = 1K$, and $\tau_\infty \in \{1K, \infty\}$. Figures 10 and 11 show the results for a cache large enough to store all approximate values ($\kappa = 50$), with cost factor $\rho = 1$ and $\rho = 4$, respectively. Figures 12 and 13 show the results for a small cache of size $\kappa = 20$, again with $\rho = 1$ and $\rho = 4$ respectively.

The performance of our algorithm with $\tau_\infty = \tau_0$ almost precisely matches the exact caching algorithm under all workloads, cache sizes, and cost configurations tested. If we set $\tau_\infty = \infty$, our algorithm offers a significant performance improvement for workloads not requiring exact precision, at

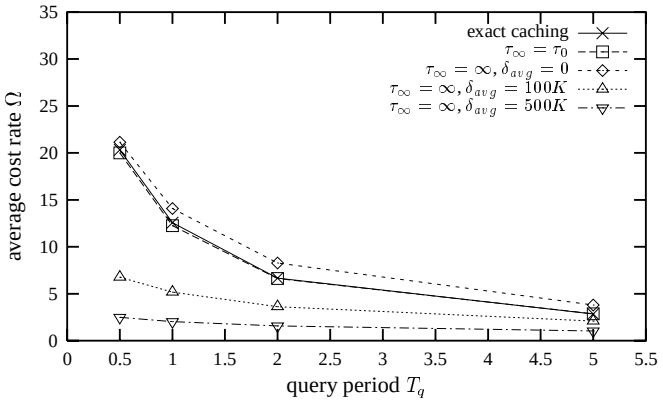


Figure 10: Comparison against exact caching, $\rho = 1$ and $\kappa = 50$.

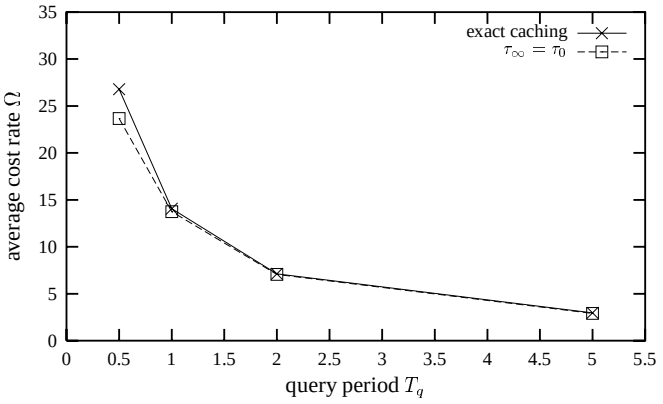


Figure 12: Comparison against exact caching, $\rho = 1$ and $\kappa = 20$.

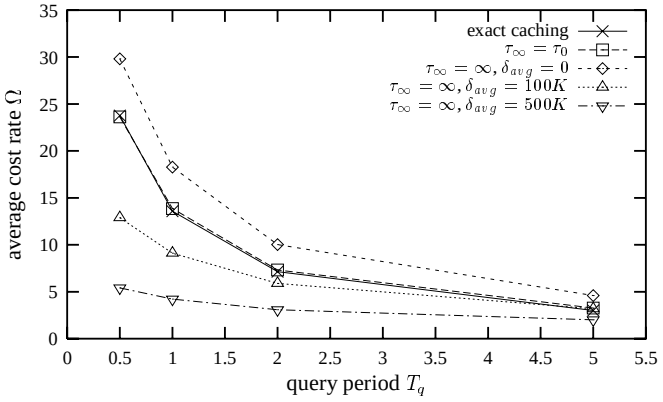


Figure 11: Comparison against exact caching, $\rho = 4$ and $\kappa = 50$.

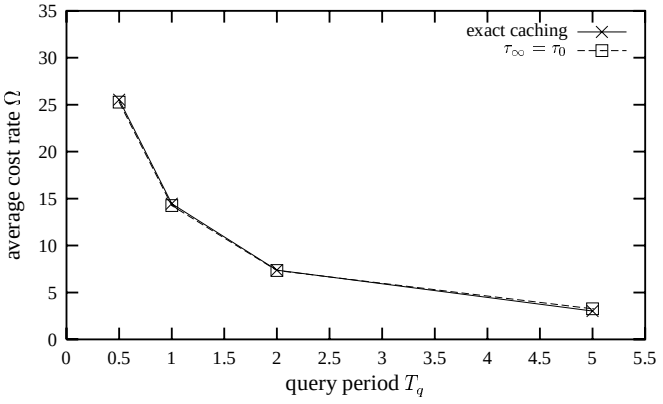


Figure 13: Comparison against exact caching, $\rho = 4$ and $\kappa = 20$.

the expense of a slight performance degradation for exact-precision workloads in the case of SUM queries, as shown in Figures 10 and 11. When MAX queries are used, our algorithm performs substantially better than exact caching because values can be eliminated as candidates for the exact maximum based on cached intervals, as discussed in Section 4.4. When the cache size is limited, as in Figures 12 and 13, queries do not benefit much from nonzero precision constraints because inexact intervals tend to be evicted from the cache.

4.7 Comparison with Divergence Caching

In Section 1.3 we discussed *Divergence Caching* [HSW94], which is the previous work most similar to ours. Recall that in Divergence Caching, *stale value approximations* are considered, where precision is inversely proportional to the number of updates to the source value not reflected in the cached approximation, independent of the actual updates. Rather than adjusting the precision incrementally as our algorithm does, the Divergence Caching algorithm continually resets the precision from scratch using detailed projections for data access and update patterns. These projections are based on past observations using a moving window scheme where the cache keeps track of the k most recent reads and the source keeps track of the k most recent writes. Based on empirical trials, the window size k was set to 23.

The Divergence Caching algorithm works well in its intended environment, but it is not clear that it could be generalized easily or effectively to incorporate update patterns as well as frequency. On the other hand, we were able to adapt our algorithm to handle stale value approximations, and we report on a preliminary performance comparison. It was a simple matter to use numeric intervals to bound the number of updates to the exact source value. We also needed to adjust our formula for the cost factor ρ to $\rho' = \frac{C_{vr}}{C_{qr}}$. Recall that in our setting, we set $\rho = 2 \cdot \frac{C_{vr}}{C_{qr}}$ based on a mathematical analysis (Appendix A). A similar (simplified) analysis of the value-initiated refresh probability in the Divergence Caching setting yields $\rho' = \frac{C_{vr}}{C_{qr}}$. No other modifications to our algorithm were necessary.

Figures 14 and 15 show an initial performance comparison of the two approaches. We varied the average precision

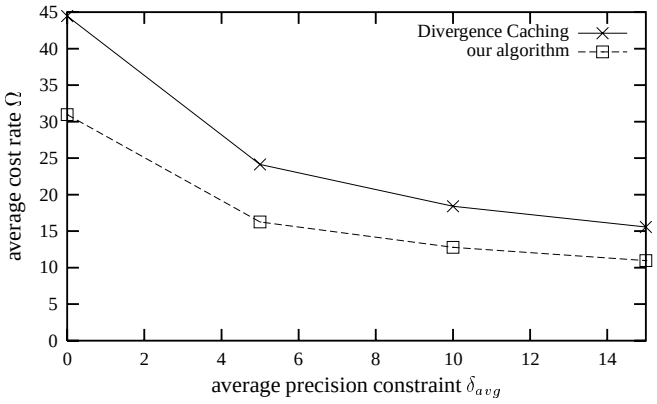


Figure 14: Comparison against Divergence Caching, $T_q = 1$.

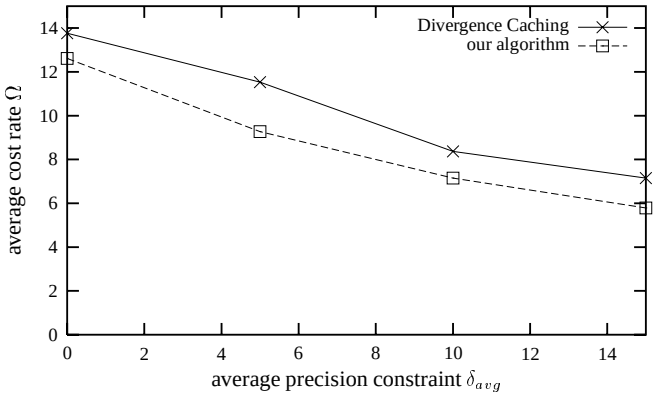


Figure 15: Comparison against Divergence Caching, $T_q = 5$.

constraint δ_{avg} (with $\Delta\delta = 1$) for two different query periods $T_q \in \{1, 5\}$. We set costs $C_{vr} = 1$ and $C_{qr} = 2$, giving $\rho' = 0.5$. For our algorithm we used $\alpha = 1$, $\tau_0 = 1$, and $\tau_\infty = 1$ when $\delta_{avg} = 0$ and $\tau_\infty = \infty$ otherwise. For the Divergence Caching algorithm we set the window size $k = 23$. We also tried other values for k but no significant performance improvements resulted. As can be seen, our algorithm shows a modest performance improvement over Divergence Caching when we specialize our algorithm to handle stale value approximations.

5 Future Work

In this paper we have considered how to set the precision of approximate values adaptively in dynamic data caching environments. As future work, we plan to investigate adaptive precision setting in symmetric replication architectures, building on work on adaptive exact replication [WJH97] and on replicating interval approximations [YV00]. We also plan to explore algorithms for setting precision in *multi-level* data caching environments, where each data object resides on one source and there is a hierarchy of caches (*e.g.*, [Ink99]). With multi-level caching, the precision of an approximation in one cache may affect the precision of derived approximations in other caches in the hierarchy. Finally, we plan to investigate how our algorithms and approximations might be applied to other forms of data. For example, environments that cache Web pages could use our approach as discussed in Section 2.1, if the deviation between the exact copy at the source and the stale cached replica can be measured numerically.

Acknowledgments

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A Estimating the Probability of Refresh

To determine the probability of each type of refresh, let us consider a simplified model. First, we model the changing data value as a random walk in one dimension. In the random walk model the value either increases or decreases by a constant amount s at each time step. A value-initiated refresh occurs when the value moves out of the cached interval approximation. Queries access the data every T_q time steps. We assume each query accesses only one data value and is accompanied by a *precision constraint* δ sampled from a uniform distribution between 0 and δ_{max}. A query-initiated refresh occurs when the cached interval's width is larger than a query's precision constraint δ. Although this model is simplified, it is useful for deriving formulas and demonstrating the principles behind our algorithm. As we show empirically in Section 4, our algorithm works well for real-world data under a variety of query workloads and precision constraints.

Using our model, we now derive expressions for the value- and query-initiated refresh probabilities at each time step, P_{vr} and P_{qr} respectively. These probabilities depend on the nature of the data and updates, the frequency of queries, and the distribution of precision constraints. The probability of a query-initiated refresh at a given time step equals the probability P_q that a query is issued, multiplied by the probability $P_{\delta<W}$ that the precision of the cached interval does not meet the precision constraint of the query. Clearly, the probability P_q that a query occurs at each time step is $P_q = \frac{1}{T_q}$. Recall that in our model, precision constraints are uniformly distributed between 0 and δ_{max}. Thus, as long as $0 \leq W \leq \delta_{max}$, $P_{\delta<W} = \frac{W}{\delta_{max}}$. Putting it all together, we have $P_{qr} = P_q \cdot P_{\delta<W} = \frac{W}{T_q \cdot \delta_{max}}$. Therefore, the probability of a query-initiated refresh is proportional to the interval width: $P_{qr} \propto W$.

Determining a formula for the value-initiated refresh probability requires an analysis of the behavior of a random walk. In the random walk model, after t steps of size s, the probability distribution of the value is a binomial distribution with variance $s^2 \cdot t$ [GKP89]. Chebyshev's Inequality [GKP89] gives an upper bound on the probability P that the value is beyond any distance k from the starting point: $P \leq t \cdot (\frac{s}{k})^2$. If we let $k = \frac{W}{2}$, and treat the upper bound as a rough approximation, we have the probability P_{vr} that the value has exceeded its interval after t time steps: $P_{vr} \approx t \cdot (\frac{2 \cdot s}{W})^2$. Therefore, the probability of a value-initiated refresh is proportional to the reciprocal of the square of the interval width: $P_{vr} \propto \frac{1}{W^2}$.