Transactional Predication: High-Performance Concurrent Sets and Maps for STM

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This paper should be considered for the best student paper award.
Nathan G. Bronson, Jared Casper, and Hassan Chafi are student authors.

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Abstract

Concurrent collection classes are widely used in multi-threaded programming, but they provide atomicity only for a fixed set of operations. Software transactional memory (STM) provides a convenient and powerful programming model for composing atomic operations, but concurrent collection algorithms that allow their operations to be composed using STM are significantly slower than their non-composable alternatives.

We introduce *transactional predication*, a method for building transactional maps and sets on top of an underlying non-composable concurrent map. We factor the work of most collection operations into two parts: a portion that does not need atomicity or isolation, and a single transactional memory access. The result approximates semantic conflict detection using the STM's structural conflict detection mechanism. The separation also allows extra optimizations when the collection is used outside a transaction. We perform an experimental evaluation that shows that predication has better performance than existing transactional collection algorithms across a range of workloads.

1. Introduction

Concurrent sets and maps classes have emerged as one of the core abstractions of multi-threaded programming. They provide the programmer with the simple mental model that most method calls are linearizable, while admitting efficient and scalable implementations. Concurrent hash tables are part of the standard library of Java and C#, and are part of Intel's Thread Building Blocks for C++. Concurrent skip lists are also widely available. The efficiency and scalability of these data structures, however, comes from the use of non-composable concurrency control schemes. None of the standard concurrent hash table or skip list implementations provide composable atomicity.

Software transactional memory (STM) provides a natural model for expressing and implementing compound queries and updates of concurrent data structures. It can atomically compose multiple operations on a single collection, operations on multiple collections, and reads and writes to other shared data. Unlike lock-based approaches, composition using transactions does not lead to deadlock or priority inversion.

If all of the loads and stores performed by a hash table, tree, or skip list are managed by an STM, then the resulting data structure automatically has linearizable methods that may be arbitrarily composed into larger transactions. The STM implementation may also provide useful properties such as: optimistic conflict detection with invisible readers (provides the best scalability for concurrent readers on cache-coherent shared memory architectures) [22]; lock- or obstruction-freedom (limits the extent to which one thread can interfere with another) [23]; intelligent contention management (prevents starvation of individual transactions) [8]; and modular blocking using using `retry` and `orElse` (allows composition of code that performs conditional waiting) [10].

We apply the adjective 'transactional' to a data structure if its operations may participate in a transaction, regardless of the underlying implementation. The most straightforward way of implementing such an algorithm is to execute all shared memory accesses through the STM; the result will automatically be transactional, but it will suffer from high single-thread overheads and false conflicts. For many applications, trading some speed for improved programmability can be a good decision. Maps and sets are such fundamental data structures, however, that the additional internal complexity and engineering effort of bypassing the STM is justified if it leads to improvements in performance and scalability for all users.

This paper introduces *transactional predication*, the first implementation technique for transactional maps and sets that preserves the STM's optimistic concurrency, contention management, and modular blocking features, while reducing the overheads and false conflicts that arise when the STM must mediate access to the internal structure of the collection. We factor each transactional operation into a referentially transparent lookup and a single STM-managed read or write. This separation allows the bulk of the work to bypass the STM, yet leaves the STM responsible for atomicity and isolation. Our specific contributions:

- We introduce transactional predication, the first method for performing semantic conflict detection for transactional maps and sets using an STM's structural conflict detection mechanism. This method leverages the existing research on STM implementation techniques and features, while avoiding structural conflicts and reducing the constant overheads that have plagued STM data structures (Section 3).
- We use transactional predication to implement transactional sets and maps on top of linearizable concurrent maps (Section 3). We add support for iteration in unordered maps (Section 5.1), and describe how to perform iteration and range-based search in ordered maps (Section 5.2).
- We describe two schemes for garbage collecting predicates from the underlying map: one based on reference counting (Section 4.1), and one using soft references (Section 4.2).
- We experimentally evaluate the performance and scalability of maps implemented with transactional predication, comparing them to best-of-breed non-transactional concurrent maps, data structures implemented directly in an STM, and concurrent maps that have been transactionally boosted. We find that predicated maps outperform existing transactional maps, often significantly (Section 6).

2. Background

Sets and associative maps are fundamental data structures; they are even afforded their own syntax and semantics in many programming languages. Intuitively, concurrent sets and maps should allow accesses to disjoint elements to proceed in parallel. There is a surprising diversity in the techniques developed to deliver this parallelism. They can be roughly grouped into those that use fine-grained locking and those that use concurrency control schemes tailored to the specific data structure and its operations. Transactional predication is independent of the details of the underlying map implementation, so we omit a complete survey. We refer the reader to [15] for step-by-step derivation of several concurrent hash table and skip list algorithms.

Concurrent collection classes are widely used, but they do not provide a means to compose their atomic operations. This poses a difficulty for applications that need to simultaneously update multiple elements of a map, or coordinate updates to two maps. Consider an application that needs to concurrently maintain both a forward and reverse association between keys and values, such as a map from names to phone numbers and from phone numbers to names. If the forward and reverse maps are implemented using hash tables with fine-grained locks, then changing a phone number while maintaining data structure consistency requires acquiring one lock in the forward map (to change the value that records the phone number), and two locks in the reverse map (to remove the name from one number and add it to another). This would require breaking the clean interface to the concurrent map by exposing its internal locks, because it is not sufficient to perform each of the three updates separately. This example also leads to deadlock if the locks are not acquired following a global lock order, which will further complicate the user's code. Lock-free hash tables don't even have the option of exposing their locks to the caller. Transactional memory, however, provides a clean model for composing the three updates required to change a phone number.

While there has been much progress in efficient execution of STM's high-level programming model, simply wrapping existing map implementations in atomic blocks will not match the performance achievable by algorithm-specific concurrency control. Data structures implemented on top of an STM face two problems:

- **False conflicts** – STMs perform conflict detection on the concrete representation of a data structure, not on its abstract state. This means that operations that happen to touch the same memory location may trigger conflict and rollback, despite the operations being semantically independent.
- **Sequential overheads** – STMs instrument all accesses to shared mutable state, which imposes a performance penalty even when only one thread is used. This penalty is a 'hole' that scalability must climb out of before a parallel speedup is observed. Sequential overheads for STM are higher than those of traditional shared-memory programming [5] and hand-rolled optimistic concurrency [2].

False conflicts between operations on a transactional data structure can be reduced or eliminated by performing *semantic conflict detection* at the level of operations. Rather than computing conflicts based on the reads from and writes to individual memory locations, higher-level knowledge is used to determine whether operations conflict. For example, adding k_1 to a set does not semantically conflict with adding k_2 if $k_1 \neq k_2$, regardless of whether those operations write to the same chain of hash buckets or rotate the same tree nodes. Because semantically independent transactions may have structural conflicts, some other concurrency control mechanism must be used to protect accesses to the underlying data structure. This means that a system that provides semantic conflict detection must break transaction isolation to communicate between active transactions. Isolation can be relaxed for accesses to the underlying structure by performing them in open nested transactions [4, 20], or by performing them outside transactions, using a linearizable algorithm that provides its own concurrency control. The latter approach is used by transactional boosting [12].

Although semantic conflict detection using open nested transactions reduces the number of false conflicts, it exacerbates sequential overheads. Accesses still go through the STM, but additional information about the semantic operations must be recorded and shared. Semantic conflict detection using transactional boosting reduces sequential overheads by allowing loads and stores to the underlying data structure to bypass the STM entirely, but it accomplishes this by adding a layer of pessimistic two-phase locking. These locks interfere with optimistic STMs, voiding useful properties such as opacity [9], obstruction- or lock-freedom, and modular blocking [10]. In addition, boosting must be tightly integrated to the STM's contention manager to prevent starvation and livelock.

The goal of our research into transactional collections is to produce data structures whose non-transactional performance and scalability is equal to the best-of-breed concurrent collections, but that provide all of the composability and declarative concurrency benefits of STM. Transactional predication is a step in that direction.

3. Transactional Predication

Consider a minimal transactional set, that provides only the functions `contains`(e) and `add`(e). Semantically, these operations conflict only when they are applied to equal elements, and at least one operation is an `add` [1]:

conflict?	`contains`(e_1)	`add`(e_1)
`contains`(e_2)	no	$e_1 = e_2$
`add`(e_2)	$e_1 = e_2$	$e_1 = e_2$

This conflict relation has the same structure as the basic reads and writes in an STM: two accesses conflict if they reference the same location and at least one of them is a write:

conflict?	`stmRead`(p_1)	`stmWrite`(p_1, v_1)
`stmRead`(p_2)	no	$p_1 = p_2$
`stmWrite`(p_2, v_2)	$p_1 = p_2$	$p_1 = p_2$

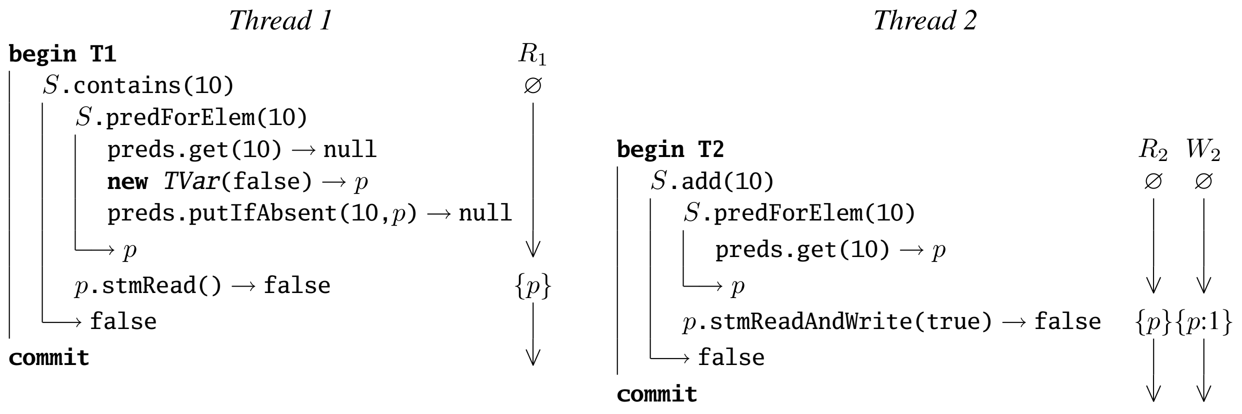
The correspondence between the conflict relations means that we can perform semantic conflict detection in our transactional set by mapping each element e to a location p, performing a read from p during `contains`(e), and performing a write to p during `add`(e).

Of course, conflict detection is not enough; operations must also query and update the abstract state of the set, and these accesses must be done in a transactional manner. Perhaps surprisingly, the reads and writes of p can also be used to manage the abstract state. Transactional predication is based on the observation that membership in a finite set S can be expressed as a predicate $f : U \to \{0, 1\}$ over a universe $U \supseteq S$ of possible elements, where $e \in S \iff f(e)$, and that f can be represented in memory by storing $f(e)$ in the location p associated with each e. We refer to the p associated with e as that element's *predicate*. To determine if an e is in the abstract state of the set, as viewed from the current transactional context, we perform an STM-managed read of p to see if $f(e)$ is true. To add e to the set, we perform an STM-managed write of p to change the encoding for $f(e)$. The set operations are trivial because the complexity has been moved to the $e \to p$ mapping.

[1] We assume that add returns a boolean indicating the previous status, so it is not idempotent.

```
 1 class TSet[A] {
 2   def contains(elem: A): Boolean = predForElem(elem).stmRead()
 3   def add(elem: A): Boolean = predForElem(elem).stmReadAndWrite(true)
 4   def remove(elem: A): Boolean = predForElem(elem).stmReadAndWrite(false)
 5
 6   private val predicates = new ConcurrentHashMap[A,TVar[Boolean]]
 7   private def predForElem(elem: A): TVar[Boolean] = {
 8     var pred = predicates.get(elem)
 9     if (pred == null) {
10       val fresh = new TVar(false)
11       pred = predicates.putIfAbsent(elem, fresh)
12       if (pred == null) pred = fresh
13     }
14     return pred
15 } }
```

Figure 1. A minimal but complete transactionally predicated set in Scala. Read and write barriers are explicit. We use the convention that *TVar* and *TArray* are provided natively by the STM, and that other types whose name is prefixed by *T* are transactional classes implemented atop the basic mutable cells and mutable arrays.



```
                    Thread 1                                              Thread 2
begin T1                                        R1
| S.contains(10)                                ∅
| | S.predForElem(10)                           |
| | | preds.get(10) → null                      |    begin T2                              R2  W2
| | | new TVar(false) → p                       |    | S.add(10)                           ∅   ∅
| | | preds.putIfAbsent(10,p) → null           |    | | S.predForElem(10)                 |   |
| | └→ p                                        ↓    | | | preds.get(10) → p               |   |
| | p.stmRead() → false                        {p}   | | └→ p                              ↓   ↓
| └→ false                                      |    | | p.stmReadAndWrite(true) → false  {p}{p:1}
commit                                          ↓    | └→ false                            |   |
                                                     commit                                ↓   ↓
```

Figure 2. A simultaneous execution of `contains(10)` and `add(10)` using the code from Figure 1. R_i and W_i are the read and write sets. Thread 1 lazily initializes the predicate for element 10.

The final piece of *TSet* is the mapping from element to predicate, which we record using a hash table. Precomputing the entire relation is not feasible, so we populate it lazily. The mapping for any particular e never changes and is independent of the rest of the system, so `predForElem(elem)` is referentially transparent; its implementation can bypass the STM entirely.

Although the mapping for each element is fixed, reads and lazy initializations of the underlying hash table must be thread-safe. Any concurrent hash table implementation may be used, as long as it provides a way for threads to reach a consensus on the lazily installed key-value associations. Figure 1 shows the complete Scala code for a minimal transactionally predicated set, including an implementation of `predForElem` that uses `putIfAbsent` to perform the lazy initialization. `putIfAbsent`(e, p) associates p with e only if no previous association for e was present. It returns `null` on success, or the existing p_0 on failure. In Figure 1, Line 11 proposes a newly allocated predicate to be associated with `elem`, and Line 12 uses the value returned from `putIfAbsent` to compute the consensus decision.

3.1 Atomicity and Isolation

Transactional predication factors the work of *TSet* operations into two parts: lookup of the appropriate predicate, and an STM-managed access to that predicate. Because the lookup is referentially transparent, atomicity and isolation are not needed. The lookup can bypass the STM completely. The read or write to the predicate requires STM-provided atomicity and isolation, but only a single access is performed and no false conflicts can result.

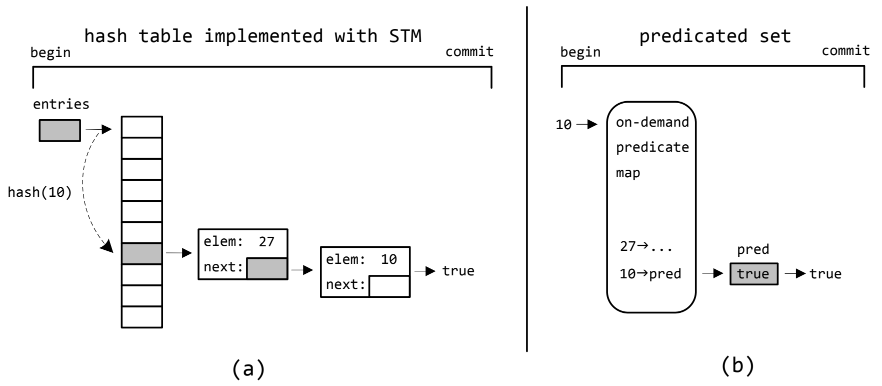


Figure 3. Execution of `contains(10)` in: a) a hash table performing all accesses to shared mutable state via STM; and b) a transactionally predicated set. ▭ are STM-managed reads.

Bypassing the STM for the predicate map is similar to Moss' use of open nesting for *`String`*`.intern(`s`)`, which internally uses a concurrent set to merge duplicate strings [19]. Like strings interned by a failed transaction, predicates installed during lazy initialization do not need to be removed during rollback.

Figure 2 shows a possible simultaneous execution of `contains(10)` and `add(10)` using the code from Figure 1. Time proceeds from the top of the figure to the bottom. Because no predicate was previously present for this key, thread 1 performs the lazy initialization of the $10 \rightarrow p$ mapping. An association is present by the time that thread 2 queries the mapping, so it doesn't need to call `putIfAbsent`. At commit time, T_1's read set contains only the element p. This means that there is no conflict with a transaction that accesses any other key of S, and optimistic concurrency control can be used to improve the scalability of parallel reads.

The abstract state of the set is completely encoded in STM-managed memory locations, so the STM provides atomicity and isolation for the data structure. Unlike previous approaches to semantic conflict detection, no write buffer or undo log separate from the STM's are required, and no additional data structures are required to detect conflicts. This has efficiency benefits, because the STM's version management and conflict detection are highly optimized. It also has semantic benefits, because opacity, closed nesting, modular blocking, and sophisticated conflict management schemes continue to work unaffected.

There are two subtleties that deserve emphasis: 1) A predicate must be inserted into the underlying map even if the key is absent. This guarantees that a semantic conflict will be generated if another transaction adds a key and commits. 2) When inserting a new predicate during `add`, the initial state of the predicate must be `false` and a transactional write must be used to set it to `true`. This guarantees that any concurrent transactions that observe the predicate before the adding transaction's commit will not see the speculative add.

3.2 Direct STM vs. Transactional Predication

Figure 3 shows how a transaction might execute `contains(10)` using two different transactional sets. In part (a) the set is presented by a hash table with chaining. To locate the element, a transactional read must be performed to locate the current hash array, then a transactional read of the array is used to begin a search through the bucket chain. Each access through the STM incurs a performance penalty, because it must be recorded in the read set and validated during commit. In addition, reads that occur to portions of the data structure that are not specific to a particular key may lead to false conflicts. In this example, `remove(27)` will conflict with `contains(10)`, even though at a semantic level those operations are independent.

Figure 3b shows how a predicated set executes `contains(10)`. A concurrent hash map lookup is performed outside the STM to locate the predicate. A single transactional read of the predicate is then used to answer the query. The abstract state is encoded entirely in these STM-managed memory locations; the mapping from key to predicate has no side effects and requires no atomicity or isolation. Thus no scheduling constraints are placed on the STM, and no separate undo log, write buffer or conflict information is needed.

3.3 Extending Predication to Maps

The predicate stores the abstract state for its associated element. The per-element state for a set consists only of presence or absence, but for a map we must also store a value. We encode this using Scala's *Option*[*V*] algebraic data type, which is Some(v) for the presence of value v, or None for absence. *TMap*[*K*, *V*] then uses predicates of type *TVar*[*Option*[*V*]]:

```
class TMap[K,V] {
  def get(key: K): Option[V] = predForKey(key).stmRead()
  def put(key: K, value: V): Option[V] = predForKey(key).stmReadAndWrite(Some(value))
  def remove(key: K): Option[V] = predForKey(key).stmReadAndWrite(None)
  private def predForKey(key: K): TVar[Option[V] = { ... }
}
```

3.4 Sharing of Uncommitted Data

Like other forms of semantic conflict detection, transactional predication must make the keys of the predicate map public before the calling atomic block has committed. Carlstrom et al. [4] propose addressing this problem by using Java's *Serializable* interface to reduce keys to byte arrays before passing them across an isolation boundary in their hardware transactional memory (HTM). The version management and conflict detection in most STMs does not span multiple objects; for these systems Moss [19] shows that immutable keys can be shared across isolation boundaries. In our presentation and in our experimental evaluation we assume that keys are immutable.

4. Garbage Collection

The minimal implementation presented in the previous section never garbage collects its *TVar* predicates. The underlying concurrent map will contain entries for keys that were removed or that were queried but found absent. While information about absence must be kept for the duration of the accessing transaction to guarantee serializability, for a general purpose data structure it should not be retained indefinitely. Some sort of garbage collection is needed.

Predicates serve two purposes: they encode the abstract state of the set or map, and they guarantee that semantically conflicting operations will have a structural conflict. The abstract state will be unaffected if we remove a predicate that records absence, so to determine if such a predicate can be reclaimed we only need to reason about conflict detection. Semantic conflict detection requires that any two active transactions that perform a conflicting operation on the predicated collection must agree on the predicate, because the predicate's structural conflict stands in for the semantic conflict. If transaction T_1 calls get(k) and a simultaneous T_2 calls put(k,v), then they must agree on k's predicate so that T_1 will be rolled back if T_2 commits.

For STMs that linearize during commit, it is sufficient that transactions agree on the predicate for k only during the interval between the transactional map operation that uses k and their commit. To see that this is sufficient, let (a_i, e_i) be the interval that includes T_i's access to k and T_i's commit. If the intervals overlap, then T_1 and T_2 agree on k's predicate. If the intervals don't overlap, then assume WLOG that $e_1 < a_2$ and that there is no intervening transaction. The predicate could not have been garbage collected unless T_1's committed state implies k is absent, so at a_2 a new empty predicate will be created. T_2's commit occurs after a_2, so T_2 linearizes after T_1. The final state of k of T_1 for k is equal to the initial abstract state for T_2, so the execution is serializable.

Algorithms that guarantee opacity can optimize read-only transactions by linearizing them before their commit, because consistency was guaranteed at the last transactional read (and all earlier ones). The TL2 [6] algorithm, for example, performs this optimization. We can provide correct execution for TL2 despite using the weaker agreement property by arranging for newly created predicates to have a larger timestamp than any reclaimed predicate. This guarantees that if a predicate modified by T_1 has been reclaimed, any successful transaction that installs a new predicate must linearize after T_1. We expect that this technique will generalize to other timestamp-based STMs. We leave for future work a formal treatment of object creation by escape actions in a timestamp-based STM. The code used in the experimental evaluation (Section 6) includes the TL2-specific mechanism for handling this issue while retaining the read-only commit optimization.

Predicate reclamation can be easily extended to include Harris et al.'s modular blocking operators **retry** and **orElse** [10]. Predicates read by a transaction awaiting **retry** are considered live.

4.1 Reference Counting

One option for reclaiming predicates once they are no longer in use is reference counting. There is only a single level of indirection, so there are no cycles that would require a backup collector. Reference counts are incremented on access to a predicate, and decremented when the enclosing transaction commits or rolls back. Whenever the reference count drops to zero and the committed state of a predicate records absence, it may be reclaimed.

Reference counting is slightly complicated by an inability to decrement the reference count and check the value of the predicate in a single step. We solve this problem by giving present predicates a reference count bonus, so that a zero reference count guarantees that the predicate's committed state records absence. Transactions that perform a `put` that results in an insertion add the bonus during commit (actually, they just skip the normal end-of-transaction decrement), and transactions that perform a `remove` of a present key subtract the bonus during commit. To prevent a race between a subsequent increment of the reference count and the predicate's removal from the underlying map, we never reuse a predicate after its reference count has become 0. Appendix A gives the code for a reference-counted transactionally predicated map. This mechanism is appealing because it keeps the predicate map as small as possible, and can be used in an unmanaged environment. It requires writes to a shared memory location, however, which can limit scalability if many transactions read the same key.

4.2 Soft References

When running in a managed environment, we can take advantage of weak references to reclaim unused predicates. Weak references can be traversed to retrieve their referent if it is still available, but do not prevent the language's GC from reclaiming the referenced object. Some platforms have multiple types of weak references, giving the programmer an opportunity to provide a hint to the GC about expected reuse. On the JVM there is a distinction between *WeakReference*s, which are garbage collected at the first opportunity, and *SoftReference*s, which survive collection if there is no memory pressure. Reclamations require mutation of the underlying predicate map, so to maximize scalability we use soft references.

Soft references to the predicates themselves are not correct, because the underlying map may hold the only reference (via the predicate) to a valid key-value association. Instead, when creating a predicate we construct a discardable token object, and add a soft reference to the token from the predicate. To guarantee that only absent predicates will be removed, we embed a strong reference to the token in each transactional state that corresponds to a present element or key-value association.

For sets, we replace the `TVar[Boolean]` with `TVar[Token]`, representing a present entry as a *Token* and an absent entry as `null`. For maps, we replace the `TVar[Option[V]]` with a `TVar[(Token,V)]`, encoding a present key-value association as `(Token,`v`)` and an absent association as `(null,*)`. If an element or association is present in any transaction context then a strong reference to the token exists. If a transactional read indicates absence, then a strong reference to the token is added to the transaction object itself, to guarantee that the token will survive at least until the end of the transaction. A predicate whose token has been garbage collected is stale and no longer usable, the same as a predicate with a zero reference count. If a predicate is not stale, transaction contexts may disagree about whether the entry is present or absent, but all contexts will agree on the transition into the stale state. Complete code for a transactional set that reclaims predicates with soft references is in Appendix B.

4.3 Optimizations for Non-Transactional Access

Ideally, transactional sets and maps would be as efficient as best-of-breed linearizable collections when used outside a transaction. If code that doesn't need STM integration doesn't pay a penalty for the existence of those features, then each portion of the program can make a local feature/performance tradeoff. Transactionally predicated maps do not completely match the performance of non-composable concurrent maps, but linearizable non-transactional operations afford several opportunities for optimization that help close the gap.

Avoiding the overhead of a transaction: The transactionally predicated sets and maps presented so far perform exactly one access to an STM-managed memory location per operation. If an operation is called outside an atomic block, we can use an isolation barrier, an optimized code sequence that has the effect of performing a single-access transaction [16]. Our scheme for unordered enumeration (Section 5.1) requires two accesses for operations that change the size of the collection, but both locations are known ahead of time. Saha et al. [22] show that STMs can support a multi-word compare-and-swap with lower overheads than the equivalent dynamic transaction.

Reading without creating a predicate: While non-transactional accesses to the predicated set or map must be linearizable, the implementation is free to choose its own linearization point independent of the STM. This means that `get(`k`)` and `remove(`k`)` do not need to create a predicate for k if one does not already exist. A predicate is present whenever a key is in the committed state of the map, so if no predicate is found then `get` and `remove` can linearize at the read of the underlying map, reporting absence to the caller.

Reading without replacing a stale predicate: `get` and `remove` can skip removal and replacement if they discover a stale predicate, by linearizing at the later of the lookup time and the time at which the predicate became stale.

Inserting a pre-populated predicate: We can linearize a `put(`k, v`)` that must insert a new predicate at the moment of insertion. Therefore we can place v in the predicate during creation, rather than via an isolation barrier.

5. Iteration and Range Searches

So far we have considered only transactional operations on entries identified by a user-specified key. Maps also support useful operations over multiple elements, such as iteration, or that locate their entry without an exact key match, such as finding the smallest entry larger than a particular key in an ordered map. Transactionally predicated maps can implement these operations using the iteration or search functionality of the underlying predicate map.

5.1 Transactional Iteration

For a transactionally predicated map M, every key present in the committed state or a speculative state is part of the underlying predicate map P. If a transaction T visits all of the keys of P, it will visit all of the keys of its transactional perspective of M, except keys added to M by an operation that starts after the iteration. If T can guarantee that no `puts` that commit before T were executed after the iteration started, it can be certain that it has visited every key that might be in M. The exact set of keys in M (and their values) can be determined by `get(`k`)` for keys k in P.

In Section 3 we perform semantic conflict detection for per-element operations by arranging for those operations to make conflicting accesses to STM-managed memory. We use the same strategy for detecting conflicts between insertions and iterations, by adding an insertion counter. Iterations of M read this STM-managed `TVar[Int]`, and insertions that create a new predicate increment it. Iterations that miss a key will therefore be invalidated.

Unfortunately, a shared insertion counter introduces a false conflict between `put(`k_1, v_1`)` and `put(`k_2, v_2`)`. This conflict could be avoided by Harris et al.'s abstract nested transactions [11] or by Ramadan et al.'s dependence-aware transactional memory [21], but we use the simpler scheme of striping the counter across multiple memory locations. Insertions increment only the value of their particular stripe, and iterations perform a read of all stripes. By fixing the binding from thread to stripe, the probability of a false conflict is kept independent of transaction size.

There is some flexibility as to when changes to the insertion count are committed. Let t_{P+} be the time at which the key was inserted into the predicate map P and t_{M+} be the linearization time of k's insertion into M. No conflict is required for iterations that linearize before t_{M+}, because k is not part of M in their context. No conflict is required for iterations that start after t_{P+}, because they will include k. This means that any iteration that conflicts with the insertion must have read the insertion counter before t_{P+} and linearized after t_{M+}. The increment can be performed either in a transaction or via an isolation barrier, so long as it linearizes in the interval $(t_{P+}, t_{M+}]$. Incrementing the insertion counter at t_{M+}, as part of the transaction that adds k to M, allows a transactionally-consistent insertion count to be computed by summing the stripes. If a removal counter is also maintained, then we can provide a transactional `size()`. Appendix C gives the code for a transactionally predicated hash table that follows this strategy, supporting both `size` and unordered iteration in transactions.

Note that optimistic iteration is likely to produce the starving elder pathology for large maps [1]. We assume that the STM's contention manager guarantees eventual completion for the iterating transaction.

5.2 Iteration and Range Search in an Ordered Map

In an ordered map, it is more likely that an iterator will be used to access only a fraction of the elements, for example to retrieve the m smallest keys. For this use case, the insertion counter strategy is too conservative, detecting conflict even when an insertion is performed that does not conflict with the partially-consumed iterator. Ordered maps and sets also often provide operations that return the smallest or largest entry whose key falls in a range. Tracking insertions only at the collection level will lead to many false conflicts for these operations.

We solve this problem by storing an insertion count in each entry of P, as well as one additional per-collection count. An entry's counter is incremented when a predicate is added to P that becomes that entry's successor, and the per-collection counter is incremented when a new minimal entry is inserted. (Alternately a sentinal entry with a key of $-\infty$ could be used.) Because these counters only protect forward traversals, a search for the smallest key $> k$ first finds the largest key $\leq k$ and then performs a protected traversal. The successor-insertion counters for the ordered map are not useful for computing `size()`, so we increment them using a non-transactional isolation barrier.

6. Experimental Evaluation

In this section we evaluate the performance of an unordered and ordered map implemented using transactional predication. We first evaluate the two predicate reclamation schemes from Section 4, concluding that soft references (Section 4.2) are the best all-around choice. We then evaluate a predicated hash table using soft reference garbage collection, comparing it to a non-composable concurrent hash map and to two alternate implementations of a transactional map. Finally, we evaluate optimistic ordered iteration in a predicated concurrent skip list.

Experiments were run on a Dell Precision T7500n with two quad-core 2.66Ghz Intel Xeon X5550 processors, and 24GB of RAM. We used the Linux kernel version `2.6.28-16-server`. Hyper-Threading was enabled, yielding a total of 16 hardware thread contexts. Code was compiled with Scala version 2.7.7. We ran our experiments in Sun's Java SE Runtime Environment, build 1.6.0_18-b13, using the HotSpot 64-Bit Server VM with compressed object pointers. We use CCSTM, a reference-based STM for Scala [3]. CCSTM uses the TL2 algorithm [6], except that write-write conflicts are detected eagerly and revalidation may be used to advance the read timestamp.

The complete source code for the experiments is available for browsing or download from
http://github.com/nbronson/ccstm/tree/master/src/test/scala/edu/stanford/ppl/ccstm/experimental.

Our experiments emulate the methodology used by Herlihy et al. [13]. Each pass consists of each thread performing 10^6 randomly chosen operations on a shared map; a new map is used for each pass. To simulate a variety of workloads, two parameters are varied: the proportion of `get`, `put` and `remove` operations, and the range from which the keys are uniformly selected. A smaller fraction of `get`s and a smaller key range both increase contention. Because `put` and `remove` are equally likely in our tests, the map size converges to half the key range. To allow for HotSpot's dynamic compilation, each experiment consists of twenty passes; the first ten warm up the VM and the second ten are timed. Each experiment was run five times and the arithmetic average is reported as the final result.

To evaluate predicate reclamation strategies, Figure 4a shows experiments using the following map implementations:

- **conc-hash** – Lea's *ConcurrentHashMap*, as included in the JVM's runtime library [18];
- **txn-pred-none** – a transactionally predicated *ConcurrentHashMap*, with no reclamation of stale predicates;
- **txn-pred-rc** – a predicated hash map that uses the reference counting scheme of Section 4.1; and
- **txn-pred-soft** – a predicated hash map that uses the the soft reference mechanism of Section 4.2.

Txn-pred-rc performs the most up-front work but is also the most aggressive about reclamation. Txn-pred-soft delays reclamation, resulting in a larger predicate map. Because the performance benefit of improved locality depends on the working set size, we show a sweep of the key range for a fixed instruction mix (80% get, 10% put and 10% remove), at minimum and maximum thread counts. The optimizations from Section 4.3 also have a large effect, so we show both non-transactional access and access in transactions that perform 64 operations.

Except for conc-hash, the non-txn experiments represent the performance of a map that *supports* transactional access, but is currently being accessed outside an atomic block. Conc-hash is faster than any of the transactional maps, at least for 1 thread. For some multi-thread non-txn experiments, however, txn-pred-none and txn-pred-soft perform better than conc-hash, despite using a *ConcurrentHashMap* in their implementation. This is because they allow a predicate to remain after its key is removed, replacing a use of conc-hash's contended segment lock with an uncontended write to a `TVar`. If the predicate is subsequently re-added, the savings are doubled. This effect appears even more prominently in Figures 5 and 4b, discussed below.

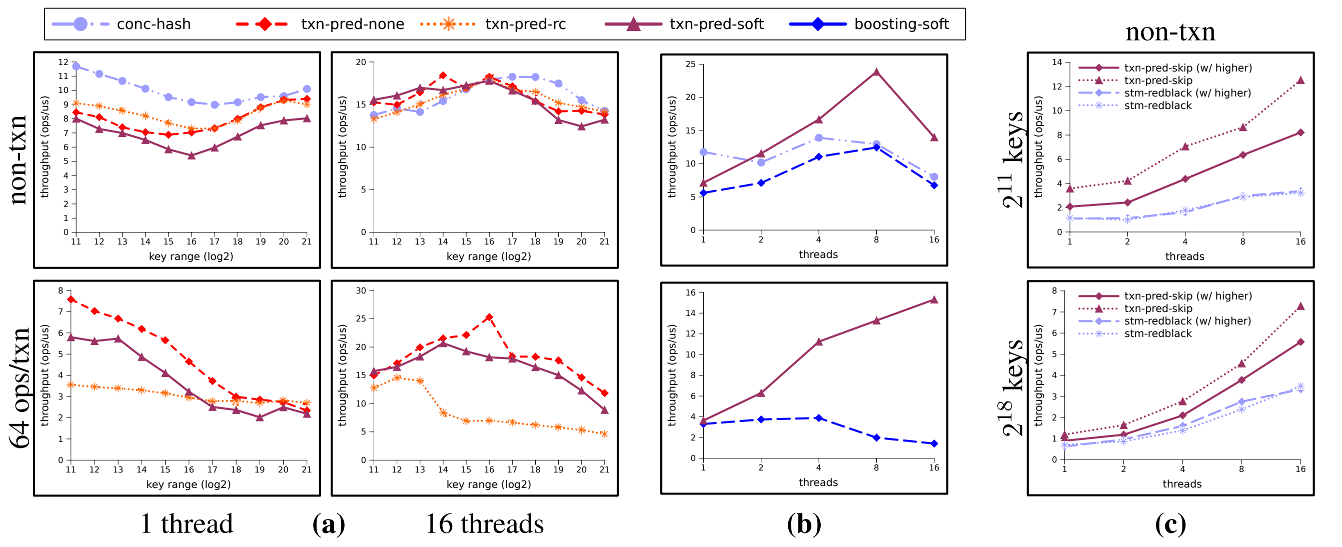


Figure 4. (a) compares the performance of three strategies for reclaiming unused predicates. Lea's non-composable *ConcurrentHashMap* is included as a reference. (b) repeats Figure 5's $\langle$non-txn, 2^{11} keys, 0% get$\rangle$ and $\langle$txn64, 2^{11} keys, 0% get$\rangle$ experiments with a scheduling policy that prefers single-chip execution. (c) evaluates ordered transactional maps by performing either 80% equality lookups (`get`), or 40% equality and 40% inequality.

For most transactional configurations (that cannot use the non-transactional optimizations) txn-pred-soft is both faster and more scalable than txn-pred-rc. The exception is uncontended (1 thread) access to a large map, where reference counting's aggressive reclamation has a locality advantage that eventually compensates for its extra work. Txn-pred-soft shows better overall performance than txn-pred-rc, so it is our default choice. Txn-pred-rc (or a dynamic selection) might be the better choice for applications that perform almost exclusively non-transactional accesses, or that have little key reuse. For the rest of the evaluation we focus only on txn-pred-soft.

Figure 5 compares the performance of txn-pred-soft to a hash table implemented via STM, and to a transactionally boosted map. Conc-hash is included in the non-transactional configurations for reference:

- **boosting-soft** – a transactionally boosted *ConcurrentHashMap*. The lock map is itself also a *ConcurrentHashMap*. Soft references are used to reclaim the locks. (Reference counting was slower for all tested configurations.)
- **stm-hash** – a chaining hash map with immutable bucket lists.

An obvious feature of most of the graphs is decreasing or constant throughput when moving from 1 to 2 threads. The default Linux scheduling policy is to spread threads across chips, which maximizes the cache capacity available to the application at the expense of high latency for writes to shared memory locations. Figure 4b shows $\langle$non-txn, 2^{11}, 0% get$\rangle$ and $\langle$txn64, 2^{11}, 0% get$\rangle$ from Figure 5, except scheduled using only a single chip if there are 8 or fewer threads. The best map throughput for these highly-contended scenarios occurs when using only a single chip. These experiments are a worst-case scenario. The overall application using transactional maps is likely to benefit from the default scheduler behavior, so we use that policy for the rest of our experiments.

Stm-hash includes several optimizations over the example used in Section 3.2. Immutable bucket chains minimize the read and write sets, a hand-rolled optimistic retry loop avoids the overhead of creating a transaction for non-transactional `get`s, and abstract nested transactions (ANT) [11] avoid rollbacks from maintenance of the load factor. The result has good single-thread overheads for the transactional experiments, but it exhibits poor scalability across all configurations. Although ANT prevents rollbacks, transactions must still serialize when inserting or removing.

Txn-pred-soft is faster than boosting-soft for every configuration we tested. For non-txn workloads, predication has two advantages over boosting: 1) The optimizations of Section 4.3 mean that txn-pred's non-transactional `get(`k`)` never needs to insert a predicate, while boosting must insert a lock for k even if k is not in the map. This effect is visible in the non-txn 80% get configurations across all thread counts. 2) Boosting's scalability is bounded by the

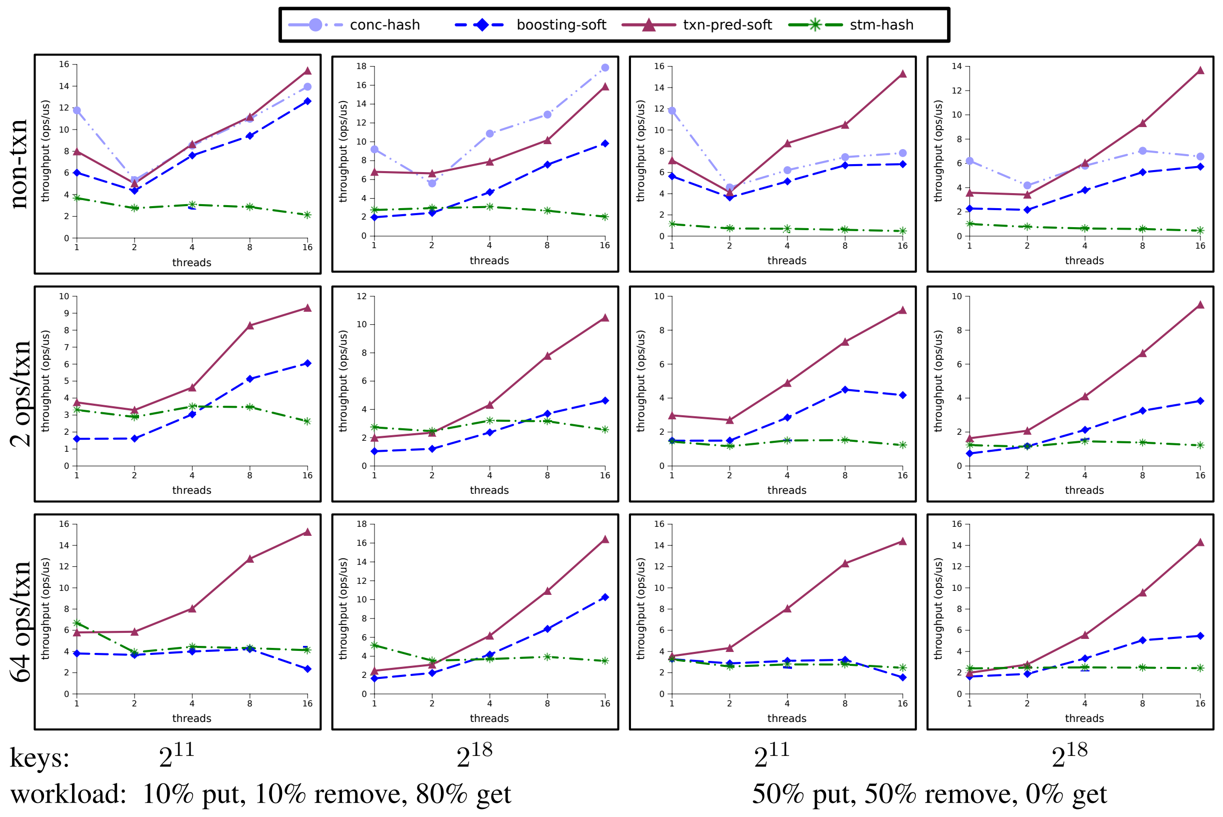


Figure 5. Performance comparison of several map implementations. Each graph plots the throughput in operations per microsecond for a particular workload, while varying the thread count from 1 to 16.

underlying *ConcurrentHashMap*. For write-heavy workloads conc-hash's 16 segment locks ping-pong from core to core during each insertion or removal, limiting scalability. Txn-pred-soft's predicates are often retained (and possibly reused) after a key is removed from the map, moving writes to lightly-contended *TVar*s. Conc-hash's bound on boosting can be clearly seen in $\langle$non-txn, 2^{11}, 0% get$\rangle$, but applies to all workloads.

Some of predication's performance advantage across all thread counts comes from a reduction in single-thread overheads. Boosting's implementation incurs a per-transaction overhead because each transaction that accesses a boosted map must allocate a side data structure to record locks and undo information, and a commit and rollback handler must be registered and invoked. Txn-pred-soft uses neither per-transaction data or transaction life-cycle callbacks. Small transactions have less opportunity to amortize boosting's overhead, so the single-thread performance advantage of predication is higher for txn2 configurations than for txn64.

The remainder of predication's performance advantage comes from its use of optimistic concurrency and its cooperation with the STM's contention management strategy. Optimistic reads provide for better scalability than boosting's pessimistic locks, which leads to pathological behavior for $\langle$64 ops/txn, 2^{11} keys, 80% get$\rangle$. (Switching to read/write locks might help this particular scenario, but it would incur extra overheads for all accesses.) CC-STM's contention manager is able to provide scalability for $\langle$64 ops/txn, 2^{11} keys, 0% get$\rangle$ despite high contention. Boosting's deadlock avoidance strategy is not integrated with the STM, impairing scalability.

Finally, we evaluate the performance of a transactionally predicated map based on a concurrent skip list, which adds optimistic ordered iteration and range searches to the key-based operations. Figure 4c compares the performance of this map to a red-black tree implemented using STM (STM skip list was slower) for two workloads with 80% reads. In the first, all reads are `get`s. In the second, half of the reads locate the smallest entry larger than the search key. Although the inequality search is slower than `get` for txn-pred-skip, predication still results in higher performance for both workloads across all thread counts.

7. Related Work

Herlihy et al. introduced early release as a method to reduce the chance of structural conflict during tree searches in their seminal paper on dynamically-sized STM [14]. Early release allows the programmer to remove elements from a transaction's read set if it can be proved that the results of the transaction will be correct regardless of whether that read was consistent. This reasoning is subtle, especially when reasoning about STM as a means for composing operations, rather than an internal data structure mechanism for implementing linearizability. Felber et al.'s elastic transactions provide the conflict reduction benefits of early release with a more disciplined model [7]. Neither of these techniques reduces the number of transactional barriers required.

Harris et al.'s abstract nested transactions (ANT) [11] allow portions of a transaction to be retried, increasing the number of transactions that can commit. ANTs could be used to insulate the caller's transaction from false conflicts that occur inside data structure operations. However, they do not avoid the need to roll back and retry the nested transaction, and add extra overheads to the base sequential case.

Semantic conflict detection using open nested transactions was described concurrently by Ni et al. [20] and Carlstrom et al. [4]. Ni et al. use open nested transactions in an STM to commit updates to transactionally managed data structures before their enclosing transaction commits, by tracking semantic conflicts with pessimistic locks. Carlstrom et al. use open nested transactions in a hardware transactional memory (HTM) to manage both the shared collection class and information about the operations performed by active transactions. This side information allows optimistic conflict detection. It is more general in form than abstract locks, and provides better fidelity than locks for range queries and partial iteration. Approaches that use open nesting still use transactions to perform all accesses to the underlying data structure, and incur additional overhead due to the side data structures and deeper nesting. This means that although they reduce false conflicts, they don't reduce the constant factors imposed by STM.

Herlihy et al. described transactional boosting [12], which addresses both false conflicts and STM constant factors. Boosting uses two-phase locking to prohibit conflicting accesses to an underlying linearizable data structure. These locks essentially implement a pessimistic visible-reader STM on top of the base STM, requiring a separate undo log and deadlock avoidance strategy. The resulting hybrid provides atomicity and isolation, but loses useful properties and features of the underlying STM, including starvation freedom for individual transactions, obstruction- or lock-freedom, modular blocking, and timestamp-based opacity. In addition, boosting requires that the STM linearize during commit, which eliminates the read-only transaction optimization possible in STMs such as TL2 [6].

Ramadan et al.'s adapt ideas from thread-level speculation in their dependence-aware transactional memory (DATM) [21]. This technique constrains the commit order when conflicts are detected, and then speculative forwards values from earlier transactions to later ones. This reduces the penalty normally imposed by false conflicts by allowing the transactions to commit anyway. Transactional predication relies only on serializability, so predicated data structures executed in an STM with DATM would allow even transactions with true semantic conflicts to be successfully serialized. In contrast, transactional boosting requires that forwarding be reimplemented at the boosting level, as in Koskinen et al's concurrent non-commutative boosted transactions [17].

8. Conclusion

This paper has introduced transactional predication, a technique for implementing high performance concurrent collections whose operations may be composed using STM. We have shown that for sets and maps we can choose a representation that allows a portion of the transactional work to safely bypass the STM. The resulting data structures approximate semantic conflict detection using the STM's structural conflict detection mechanism, while leaving the STM completely responsible for atomicity and isolation. Predication is applicable to unordered and ordered sets and maps, and can support optimistic iteration and range queries.

Users currently face a difficult tradeoff between the better programmability of transactional memory's high level model and the better performance of non-composable concurrent collections; transactional predication narrows this gap. Predicated collections are faster than existing transactional algorithms across a wide range of workloads, offer good performance when used outside a transaction, and do not interfere with the underlying STM's opacity, modular blocking or contention management.

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Appendices

A. Reference Counting Code

Reference counting is used to reclaim unused predicates in a transactionally predicated map, as described in Section 4.1. Successful insertions leave their `enter` dangling, and successful removals `exit` twice, so only predicates for absent keys can become stale. Once the reference count reaches zero a predicate is not reused.

```
class Pred[V](@volatile var refCount: Int) extends TVar[Option[V]](None) {
  def refCountCAS(v0: Int, v1: Int): Boolean = { ... }
}
class THashMap_RC[K,V] {
  def get(k: K): Option[V] = {
    val p = enter(k)
    txn.afterCompletion(_ => exit(k, p, 1)) // completion is commit or rollback
    p.stmRead()
  }
  def put(k: K, v: V): Option[V] = {
    val p = enter(k) // delay scheduling end-of-txn exit until we know delta
    val prev = try {
      p.stmReadAndWrite(Some(v))
    } catch {
      case x => exit(k, p, 1); throw x // STM rollback is encoded as an exception
    }
    if (prev.isEmpty)
      txn.afterRollback(_ => exit(k, p, 1)) // bonus cancels on commit
    else
      txn.afterCompletion(_ => exit(k, p, 1))
    prev
  }
  def removeKey(k: K): Option[V] = {
    val p = enter(k) // delay scheduling end-of-txn exit until we know delta
    val prev = try {
      p.stmReadAndWrite(None)
    } catch {
      case x => exit(k, p, 1); throw x // STM rollback is encoded as an exception
    }
    if (!prev.isEmpty)
      txn.afterCompletion(t => exit(k, p, if (t.isCommitted) 2 else 1))
    else
      txn.afterCompletion(_ => exit(k, p, 1))
    prev
  }

  private val predicates = new ConcurrentHashMap[K,Pred[V]]
  private def enter(k: K) = enter(k, predicates.get(k))
  private def enter(k: K, p: Pred[V]): Pred[V] = {
    if (p != null) {
      val rc = p.refCount // p is stale if rc == 0
      if (rc > 0) {
        if (p.refCountCAS(rc, rc+1)) return p // success
        return enter(k, p) // try again with this predicate
      }
      predicates.remove(k, p) // only removes if k still maps to p
    }
    val fresh = new Pred[V](1) // pre-entered
    val repl = predicates.putIfAbsent(k, fresh)
    if (repl == null) return fresh // success
    return enter(k, repl) // try to enter the replacement
  }
  private def exit(k: K, p: Pred[V], delta: Int) {
    var rc = 0
    do { rc = p.refCount } while (!p.refCountCAS(rc, rc - delta))
    if (rc - delta == 0) predicates.remove(k, p)
  }
}
```

B. Soft Reference Code

Code for managing predicates using soft references, as described in Section 4.2. *TokRef*.cleanup() is called from a daemon thread after its referent *Token* has been collected.

```
class Token {}
class TokRef[K,V](preds: ConcurrentMap[K,Pred[V]], key: K, t: Token
    ) extends CleanableRef[Token](t) {
  var pred: Pred[V] = null
  def cleanup(): Unit = preds.remove(key, pred)
}
class Pred[V](val softRef: TokRef[_,V]) extends TVar[(Token,V)]((null, nullV)) {
  softRef.pred = this
}

class THashMap_Soft[K,V] {
  def get(key: K): Option[V] = predForKey(key).stmRead()
  def put(key: K, value: V): Option[V] = predForKey(key).stmReadAndWrite(Some(value))
  def remove(key: K): Option[V] = predForKey(key).stmReadAndWrite(None)

  private val predicates = new ConcurrentHashMap[K,Pred[V]]
  private def predForKey(k: K) = {
    val p = predicates.get(k)
    if (p == null) createPred(k) else enterPred(k, p)
  }
  private def enterPred(k: K, p: Pred[V]) = {
    val t = p.softRef.get
    if (t != null) {
      Txn.current().addStrongRef(t)
      (p,t)
    } else {
      predicates.remove(k, p)
      createPred(k)
    }
  }
  private def createP(k: K): (Pred[V],Token) = {
    val t = new Token
    val fresh = new Pred(new TokRef(predicates, k, t))
    val p = predicates.putIfAbsent(k, fresh)
    if (p == null) {
      (fresh,t)
    } else {
      enterPred(k, p)
    }
  }
}
```

C. Unordered Iteration Code

Adding optimistic iteration to a transactionally predicated unordered map by counting insertions and removals, as described in Section 5.1. To minimize conflicts between writers, the counts are striped across multiple memory locations.

```
class TMap[K,V] {
  private def numStripes = 16
  private val insertCts = Array.fromFunction(_ => { new TVar(0) })(numStripes)
  private val removeCts = Array.fromFunction(_ => { new TVar(0) })(numStripes)
  ...
  def size: Int = {
    insertCts.map(_.stmRead()).reduceLeft(_ + _) -
        removeCts.map(_.stmRead()).reduceLeft(_ + _)
  }

  private def stripeIncr(a: Array[TVar[Int]]): Unit = {
    val c = a(Thread.currentThread.hashCode() & (numStripes - 1))
    c.stmWrite(c.stmRead() + 1)
  }

  def put(key: K, value: V): Option[V] = {
    val prev = predForKey(key).stmReadAndWrite(Some(value))
    if (prev == None) stripeIncr(insertCts)
    prev
  }

  def remove(key: K): Option[V] = {
    val prev = predForKey(key).stmReadAndWrite(None)
    if (prev != None) stripeIncr(removeCts)
    prev
  }

  def elements = new Iterator[(K,V)] {
    private val iter = {
      for (c <- insertCts) c.stmRead()
      predicates.entrySet().iterator
    }
    private var avail = step()

    def hasNext: Boolean = avail != null
    def next(): (K,V) = { val z = avail; avail = step(); z }

    private def step(): (K,V) = {
      if (!iter.hasNext()) {
        null
      } else {
        val e = iter.next()
        e.getValue.stmRead() match {
          case Some(v) => (e.getKey, v)
          case None => step()
        }
      }
    }
  }
}
```