Technical Report of iZENELib

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Abstract

This document presents the technical report for the project *iZENELib* that could be used in the search engine developing process. *iZENELib* is expected to contain two parts:AM-Lib, which takes charge of storage, and IR-Lib, which takes charge of information retrieval and machine learning.

Contents

1 Document History

Date	Author	Description
2008-11-02	Kevin	Initialize the design issue of AM-Lib.
2008-11-10	Yingfeng	Initialize the design issue of IR-Lib.
2008-11-10	Yingfeng	Create the technical report.
2008-11-21	Yingfeng	Add the design issue of Matrix Library.
2008-12-05	Yingfeng	Adjust the milestone.
2008-12-19	peisheng	Update KeyType, ValueType and DataType description.
2009-02-27	Kevin	Cache-concious hash table, B-trie and dynamic perfect hash
2009-03-18	Kevin	An external sort: AlphaSort.
2009-04-30	Kevin	Map, dynamic string array
2009-06-11	Kevin	3 types of string
2009-07-22	Kevin	Duplicate detection
2009-09-24	Kevin	Trie indexer

2 Design Goal

iZENELib plans to provide a collection of utilities which could be used in the search engine developing process. *iZENELib* is expected to be composed of two parts—the part taking charge of storage(AM-Lib), and the part in charge of information retrieval and machine learning(IR-Lib). AM-Lib is expected to be composed of two sub-parts, the one which provides common utilities for data storage, and the one providing corpus data management which serves for the IR-Lib. Generic design would be adopted largely in *iZENELib* to provide much more flexibility for component's reusing.

3 Access Methods Library Design

3.1 Requirements

The future probable usages of AM-lib can be illustrated in several ways.

- In your project, you may want to compare the performance of using several different data structures. AM-lib makes this easy anyway.

```
#include "am/am.hpp''
class MyClass {

public:
        MyClass(AccessMethods<int, string>* pAm): pAm_(pAm){}

        void myFoo()
        {
                pAm_->insert(128, ``Hello! AM-lib``);
                pAm_->getDataBy(128);
                . . .
        }

private:
        AccessMethods<int, string>* pAm_;
}

////////////////////////////////////
#include "myclass.hpp''
#include "am/btree.hpp''
#include "am/rtree.hpp''
#include "am/am.hpp''
int main()
{
        AccessMethods<int, string>* pAm = new BTree<int, string>(...);
        MyClass test1(pAm);
        test1.myFoo();
        delete pAm;
        . . .
        pAm = new RTree<int, string>(...);
        MyClass test2(pAm);
        test2.myFoo();
        delete pAm;
        . . .
}
```

- You can make your modules more reuseable.

```
template<typename AmType>
void foo(AmType& am)
{
        am.insert(128, ``Hello! AM-lib``);
        am.getDataBy(128);
}

////////////////////////////////////
#include "am/btree.hpp''
#include "am/rtree.hpp''
int main()
{
        BTree<int, string> btree;
        foo(btree);
        . . .
        RTree<int, string> btree;
        foo(btree);
        . . .
}
```

- You don't need to worry about the size of data, cause AM-lib will use disk when data size comes very large.

```
                void foo(AmType& am)
                {
//initialize a 3 dimensions dynamic array
                        MulDimDynArray largeArray(100000000, 100000000, 1000000);
                        MulDimDynArray smallArray(10, 10, 10);
                        smallArray.append(largeArray);
                        . . .
                }
```

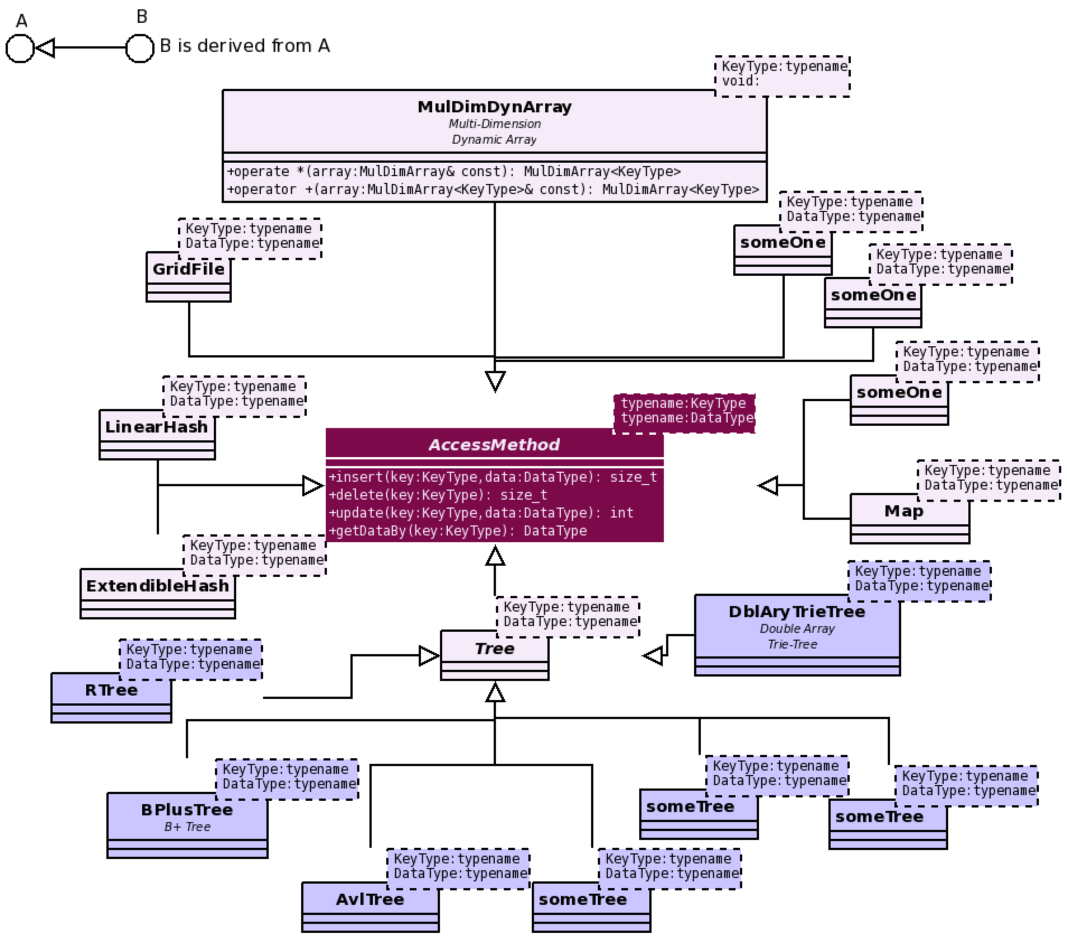


Figure 1: Initial design of AM-lib classes

3.2 Summery of exiting library

As Figure 3 shows, YLIB is a great work which includes 5 parts as algorithm, container, database, data processor and network. And SML focuses on how to deal with corpus and categorize. SF1Lib is a new library focuses on manipulating database. Our work is giving these library a new face using generic programming. For so many modules and classes in these library, just a few of them relates with the concept access methods. And we conclude the basic functions of AM is QUID (querying, updating, insertion and deletion). Policy-

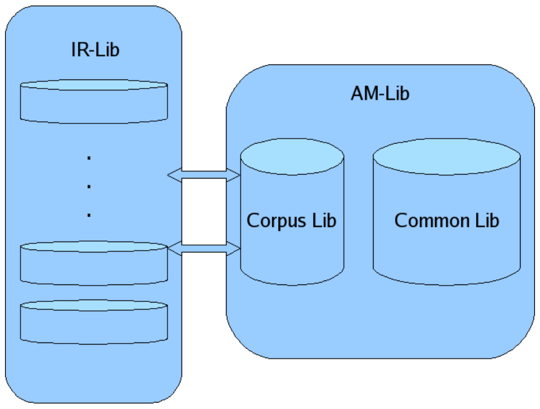


Figure 2: AM-Lib and IR-LIB

based design in book 'Modern C++ Design: Generic Programming and Design Patterns Applied' gives us a very good clue to do this work.

3.3 Policy-based AM

Policy-based design treats every changeable parts as a policy and integerates all the policies in a host which is treated as an interface for application developers and coordinates all the policies to give the functions. What a user of policy-based designed library need to know is what kind of policy he wants to use and where's the host class. Thus, what are the changeable parts of AM-Lib? They are the place to store the data, main memory or disk, if data stored on disk, the type of cache used, and data type, key type, and the container with different algorithms. We can divide access methods and data structure into two parts. One is some kind of easy data structure without specific algorithms like vector, list etc. The other is some complex structure like tree and table with some certain algorithm. The design of these two parts should be different but their interface to the client should be the same. The simple data structure could be like follow.

```
template<typename KeyType, typename ValueType,
    typename LockType=NullLock, typename Alloc=std::allocator<DataType<KeyType,ValueType> > >
class AccessMethod
{
public:
virtual bool insert(const KeyType& key, const ValueType& value);

virtual bool insert(const DataType<KeyType,ValueType>& data) = 0;

virtual bool update(const KeyType& key, const ValueType& value);

virtual bool update(const DataType<KeyType,ValueType>& data) = 0;

virtual ValueType* find(const KeyType& key) = 0;

virtual bool del(const KeyType& key) = 0;
};

template<typename KeyType, typename LockType=NullLock,typename Alloc=std::allocator<DataType<KeyType> > >
class UnaryAccessMethod
{
public:
virtual bool insert(const KeyType& key);

virtual bool insert(const DataType<KeyType>& data) = 0;

virtual bool update(const KeyType& key);
```

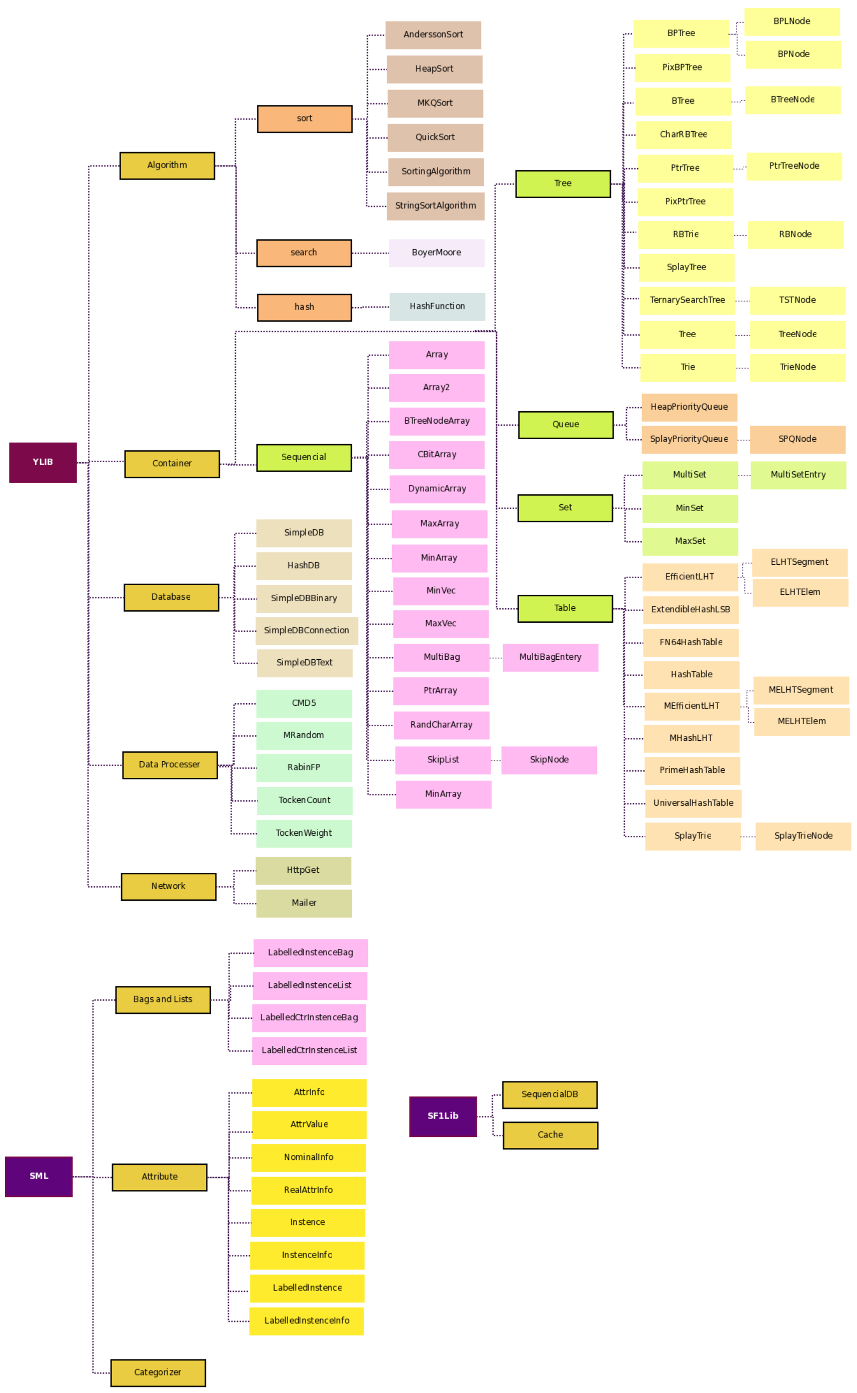


Figure 3: Summery of exiting library

```
virtual bool update(const DataType<KeyType>& data) = 0;

virtual KeyType* find(const KeyType& key) = 0;

virtual bool del(const KeyType& key) = 0;
};
```

All binary components of *AM-LIB* should implement the interface of AccessMethod while all unary components should implement the interface of , where LockType is the thread policy which allows for different threading model to be applied, Alloc is the memory policy, which we could choose to store elements in memory or file. The elements of the *AM-LIB* are **DataType**, which contains **KeyType** and **ValueType**, when **ValueType** is **NullType**(defined below), it is unary.

DataType provide **get_key()**, **get_value()**, **serialize()**, and **compare()** method.

```
struct NullType{
};

//When ValueType is NullType, it is equivatent to unary DataType.
template<typename KeyType, typename ValueType=NullType>
class DataType
{
public:
    DataType(){ }
    DataType(const KeyType& key, const ValueType& value)
    :key(key), value(value)
    {
    }

    int compare(const DataType& other) const
    {
        return _compare(other, static_cast<boost::is_arithmetic<KeyType>*>(0));
    }

    template<class Archive>
    void serialize(Archive& ar, const unsigned int version)
    {
        ar & key;
        ar & value;
    }
    const KeyType& get_key() const {return key;}

    const ValueType& get_value() const {return value;}
private:
    int _compare(const DataType& other, const boost::mpl::true_*) const
    {
        return key-other.key;
    }
    int _compare(const DataType& other, const boost::mpl::false_*) const
    {
        BOOST_CONCEPT_ASSERT((KeyTypeConcept<KeyType>));
        return key.compare(other.key);
    }

public:
    KeyType key;
    ValueType value;
};

template<typename KeyType>
class DataType<KeyType, NullType>
{
public:
    DataType(){}
    DataType(const KeyType& key)
    :key(key)
    {
    }
    DataType(const KeyType& key, const NullType&)
    :key(key)
    {}

    int compare(const DataType& other) const
    {
        return _compare(other, static_cast<boost::is_arithmetic<KeyType>*>(0));
    }
    template<class Archive>
    void serialize(Archive& ar, const unsigned int version)
    {
        ar & key;
    }

    const KeyType& get_key() const {return key;}


private:
    int _compare(const DataType& other, const boost::mpl::true_*) const
    {
        return key-other.key;
    }

    int _compare(const DataType& other, const boost::mpl::false_*) const
    {
        BOOST_CONCEPT_ASSERT((KeyTypeConcept<KeyType>));
        return key.compare(other.key);
    }

public:
    KeyType key;
};
```

As for meta type **keyType** like int, float that don't have **compare()** method, a default CompareFunctor is also provided.

```
template<class KeyType>
class CompareFunctor:public binary_function<KeyType, KeyType, int>

{
public:
    int operator()(const KeyType& key1, const KeyType& key2) const
    {
        return _compare(key1, key2, static_cast<boost::is_arithmetic<KeyType>*>(0));
    }
private:
    int _compare(const KeyType& key1, const KeyType& key2,  const boost::mpl::true_*) const
    {
        return key1 - key2;
    }

    int _compare(const KeyType& key1, const KeyType& key2,  const boost::mpl::false_*) const
    {
        BOOST_CONCEPT_ASSERT((KeyTypeConcept<KeyType>));
        return key1.compare(key2);
    }
};
```

All components of *AM-LIB* share the same definition of element—DataType.

Some kind of complex DSs (data structures) are different. The data manipulated by these DSs are composited of key and data. They have their own algorithms for sorting and searching. And for some complex situations, the key could be multiple.

```
//Library code
template
<
         class KeyType,
         class DataType,
         class StorageStrategy = MemStorage//if data size is very large,
                                          //we need to change it into DiskStorage
>
class BPTree;
///////////////////////////////////////////
template
<
         class KeyType,
         class DataType,
         class StorageStrategy = MemStorage
>
```

```
class HashTable;
////////////////////////////////////////
. . .
//////////The main class for these complex data structure/////////
template
<
        template<class> class KeyTypeList,
        class DataType,
        template<class, class, class> class ConcreteDS,
        class StorageStrategy = MemStorage
>
class ComplexAccessMethod : public ConcreteDS<KeyTypeList<ConcreteDS>, StorageStrategy>;
```

3.4 Storage Manager

3.4.1 Memory Management

Most of the C++ programmers do not benefit from 'Garbage Collection' technique (GC). They are sick of deleting objects but have to do this. There are some C/C++ memory GC implementations, but they are complex and are not widely used. Although we have smart pointer which is based on 'Reference Counting', it is not always a good idea however:

- It's a fact that not all of the C++ programmers like smart pointers, and not all of the C++ programmers like the SAME smart pointer. You have to convert between normal pointers and smart pointers, or between one smart pointer and another smart pointer. Then things become complex and difficult to control.
- Having a risk of Circular Reference.
- Tracking down memory leaks is more difficult

Therefore it is recommended to introduce the *GCAllocator* included by *StdExt* when allocating small objects. The detailed design and usage of *GCAllocator* could be got from another document—*GCAllocator.pdf*, written by *Xushiwei*—author of *GCAllocator*. It has been improved and some bugs have been fixed, locating at *izenelib/include/3rdparty/boost/memory.*

3.4.2 File Management

Since there might be lots of data structures that are required to provide a file based version to make data persistent, it is reasonable to provide a good file management mechanism to accelerate the development of file based version. *iZENELib* has provided two kinds of utilities to satisfy this requirement.

BlockManager *STXXL* is an extremely high efficient file based container, where there exists a file block manager inside, together with an asynchronous I/O layer(AIO).The purpose of the AIO layer is to provide a unified approach to asynchronous I/O. The layer hides details of native asynchronous I/O interfaces of an operating system and has the following advantages:

1. To issue read and write requests without having to wait for them to be completed.
2. To wait for the completion of a subset of issued I/O requests.
3. To wait for the completion of at least one request from a subset of issued I/O requests.
4. To poll the completion status of any I/O request.
5. To assign a callback function to an I/O request which is called upon I/O completion (asynchronous notification of completion status), with the ability to co-relate callback events with the issued I/O requests.

STXXL has a high performance on disk I/O, its I/O counterpart has been extracted independently to the *BlockManager* in *iZENELib*.However, it has the limitation of being able to process data with fixed length only. *BlockManager* is just a file block manager, with a *LRU* cache policy inside and an AIO layer, if it was adopted, still lots of work are needed, such as, how to manage data location,how to design cache,etc, however, these works are relevant to different application, which can not be easily abstracted to a common utility.

File Based Allocator Another policy of file management is to provide a file based allocator, having the same interface as such memory allocators as *std::allocator*, therefore, if an application is designed based on allocators, the according file based version is very easy to implement–just replace the original temlate parameter having value of *std::allocator* with the file based allocator. The only available mechanism of implementing such an allocator is to recur to a function provided by operating system—file mapping.Both *UNIX* like operating system and *Windows* have provided such an ability, with *mmap* for the former, *OpenFileMapping* for the latter. Under 32bit environment, there exists a limitation that only 2G bytes could be mapped into the virtual memory address at one time, therefore, for larger file, it is inconvenient to manage larger file. Under 64bit environment, such a limitation has been trivial because the virtual memory address is large enough. We have two choices for such kind of file based allocator—the one provided by *Boost* and the one provided by *iZENELib*. Take the former as the example:

```
#include <boost/interprocess/containers/list.hpp>
#include <boost/interprocess/managed_mapped_file.hpp>
#include <boost/interprocess/allocators/allocator.hpp>

using namespace boost::interprocess;
typedef list<int, allocator<int, managed_mapped_file::segment_manager> >  MyList;
int main ()
{
   const char *FileName       = "file_mapping";
   const std::size_t FileSize = 10000;
   std::remove(FileName);
   managed_mapped_file mfile_memory(open_or_create, FileName, FileSize);
   MyList * mylist = mfile_memory.construct<MyList>("MyList")(mfile_memory.get_segment_manager());

   //Obtain handle, that identifies the list in the buffer
   managed_mapped_file::handle_t list_handle = mfile_memory.get_handle_from_address(mylist);
   //Fill list until there is no more room in the file
   try{
      while(1) {
         mylist->insert(mylist->begin(), 0);
      }
   }
   catch(const bad_alloc &){
      //mapped file is full
   }
   //Let's obtain the size of the list
  std::size_t old_size = mylist->size();
   //To make the list bigger, let's increase the mapped file
   //in FileSize bytes more.
   mfile_memory.grow(FileName,FileSize);
   //If mapping address has changed, the old pointer is invalid,
   //so use previously obtained handle to find the new pointer.
   mylist = static_cast<MyList *>(mfile_memory.get_address_from_handle(list_handle));
   //Fill list until there is no more room in the file
   try{
      while(1) {
         mylist->insert(mylist->begin(), 0);
      }
   }
   catch(const bad_alloc &){
      //mapped file is full
   }
   //Let's obtain the new size of the list
   std::size_t new_size = mylist->size();
   assert(new_size > old_size);
   //Destroy list
```

```
    std::cout<<"old size "<<old_size<<std::endl;
    mfile_memory.destroy_ptr(mylist);
    return 0;
}
```

As shown above, file mapper in *Boost* is not so convenient because the length of the file has to be sure at first, and if the file space has been exhaust, the programmer has to increase the file mapping size manually. The essential design aim of the utility provided by *Boost* is to satisfy the inter process communication, therefore, the designer has not considered much about how to apply file mapping to storage design, that is why *iZENELib* still provides another implementation.With this implementation, the file could grow its size automatically, and a file space garbage collection is also provided. It is extremely easy to use, for example:

```
template<class T>
class vector : public std::vector<T, izenelib::am::allocator<T> >{};
```

With the above codes, we then have a file based vector, which has the same usage as *std::vector*.What's more, according to the benchmark testing, the file based container can perform even faster then its according memory version, following is the bench result between file mapping and *STL* containers given a data set with 1000000 items:

	Insert	Sequential Read	Random Read	Delete
filemapper	1710ms	1310ms	1870ms	780ms
std containerr	1660ms	1300ms	1910ms	790ms

iZENELib has also provided the *new* and *delete* operation to construct and destroy the object within the file space.

3.5 Dynamic String Array

When we want to store a lot of strings, first one comes into our mind is using std::vector to store std::string. Is that our only choice? No. Nikolas Askitis and Justin Zobel told us there's another way to store string array. Our idea is to store the strings in a contiguous dynamic array. Each array can be seen as a resizable bucket. The strings in a bucket are stored contiguously, which guarantees that access to the start of the bucket will automatically fetch the next 64, 128, or 256 (cache-line) bytes of the bucket into cache. With no pointers to traverse, pointer chasing is eliminated and with contiguous storage of strings, hardware prefetching schemes are highly effective. Access locality is therefore maximized, creating a cache-conscious alternative to compact and standard chains. Figure 4 shows how it organized. The dynamic array eliminates all pointers and stores strings, in order of occurrence, contiguously in a resizable array or bucket. Strings are length-encoded to permit word skipping, which is cache-efficient. The null character serves as the end-of-bucket flag.

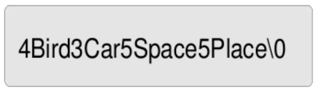


Figure 4: The strings Bird, Car,Space, and Place, are stored in a dynamic string array

The simplest way to traverse a bucket (a dynamic array) is to inspect it one character at a time, from beginning to end, until a match is found. Each string in a bucket must be null terminated and a null character must follow the last string in a bucket to serve as the end-of-bucket flag. However, this approach can cause unnecessary cache misses when long strings are encountered; note that, in the great majority of cases, the string comparison in the matching process will fail on the first character. Instead, we have used a skipping approach that allows the search process to jump ahead to the start of the next string. With skipping, each string is preceded by its length; that is, they are length-encoded. The length of each string is stored in either one or two bytes, with the lead bit used to indicate whether a 7-bit or 15-bit value is present. It is generally not sensible to store strings of more than 2^15 characters, as mandatory string-processing tasks, such as hashing, will utterly dominate search costs.

We explored two methods at growing buckets: exact-fit and paging. In exact-fit, when a string is inserted, the bucket is resized by only as many bytes as required. This conserves memory but means that copying may be frequent. Resizing a bucket involves creating a new bucket that can fit the old bucket and the string required. The old bucket is then copied, character by character, into the new bucket; the new length-encoded string is appended followed by the end-of-bucket flag. The old bucket is then destroyed.

In paging, bucket sizes are multiples of 64 bytes, thus ensuring alignment with cache lines. As a special case, buckets are first created with 32 bytes, then grown to 64 bytes when they overflow, to reduce space wastage when the bucket contains only a few strings. When grown, the old bucket can be copied into the new, a word (4 bytes) at time. Paging should reduce both the copying and computational overhead of bucket growth, but uses more memory. The value of 64 bytes was chosen to match the L1 cache-line size found in current Intel Pentium processors.

Here's some of our test experiments result. We generate 10 million random strings, and compare run-time of pushing back, looking up, serialization with deserialization, sorting and iterating with std::vector of std::string. The table 1 shows the result. All the numbers in table indicate how many seconds it needs. For pushing back and serialization, dynamic string array is much faster. There're two situations for iterating and insertion. Std::vector needs different run-time for iterating and insertion before and after being sorted. After being sorted, it needs much more time to iterate and insertion. We use "/" to separate. The front one indicate before being sorted. The back one indicate after being sorted. For insertion, we only use 100 strings, which is very time consuming. For looking up, we only look up 1000 strings, and run time of std::vector is out of acception.

Table 1: Run-time comparasion

	push back	**serialization**	**insertion**	**lookup**	**sort**	**iterate**
std::vector	2.66	5.62	47.6/178.53	NaN	27.69	0.47/1.81
dynamic array	1.97	0.67	22.98	19.75	29.66	0.86

3.6 Minimal Perfect Hashing

Minimal perfect hashing(MPH) could be divided into two categories–order-preserving and non order-preserving. Order-preserving is more useful in information retrieval, however, more research results have been got on non order-preserving solutions. Both of the MPH would be added into *iZENELib*. Like B-Tree component, MPH also provides an iterator for sequential access.

3.7 Dynamic Perfect Hashing

3.7.1 Perfect hashing

Although hashing is most often used for its excellent expected performance, hashing can be used to obtain excellent worst-case performance when the set of keys is static: once the keys are stored in the table, the set of keys never changes. Some applications naturally have static sets of keys: consider the set of reserved words in a programming language, or the set of file names on a CD-ROM. We call a hashing technique perfect hashing if the worst-case number of memory accesses required to perform a search is O(1). The basic idea to create a perfect hashing scheme is simple. We use a two-level hashing scheme with universal hashing at each level. Figure 5 illustrates the approach.

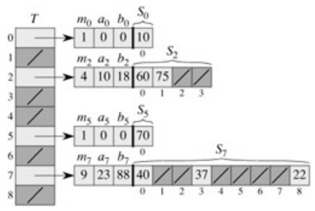


Figure 5: Perfect hash table

As Figure 5 show, it uses perfect hashing to store the set K = 10, 22, 37, 40, 60, 70, 75. The outer hash function is $h(k) = ((ak + b)modp)\ mod\ m$, where $a = 3$, $b = 42$, $p = 101$, and $m = 9$. For example, $h(75) = 2$, so key 75 hashes to slot 2 of table T . A secondary hash table S_j stores all keys hashing to slot j . The size of hash table S_j is m_j , and the associated hash function is $h_j(k) = ((a_j k + b_j)\ mod\ p)\ mod\ m_j$. Since $h_2(75) = 1$, key 75 is stored in slot 1 of secondary hash table S_2. There are no collisions in any of the secondary hash tables, and so searching takes constant time in the worst case.

The first level is essentially the same as for hashing with chaining: the n keys are hashed into m slots using a hash function h carefully selected from a family of universal hash functions. Instead of making a list of the keys hashing to slot j, however, we use a small secondary hash table S_j with an associated hash function h_j. By choosing the hash functions h_j carefully, we can guarantee that there are no collisions at the secondary level. In order to guarantee that there are no collisions at the secondary level, however, we will need to let the size m_j of hash table S_j be the square of the number nj of keys hashing to slot j. While having such a quadratic dependence of m_j on n_j may seem likely to cause the overall storage requirements to be excessive, we shall show that by choosing the first level hash function well, the expected total amount of space used is still $O(n)$.

3.7.2 Dynamic perfect hashing

This work is based on Martins paper Dynamic Perfect Hashing: Upper and Lower Bonds in 1990. During indexing, when conflict happens, it partially re-hashes data in this slot with some random chosen hash function until find a hash function that no conflicts happen in this slot. Martin proved that at least half of the hash functions in random hash function set can do it. Random hash function means choosing parameters a, b, p. When the hash table is full (defined by Martin), it needs rehash all the table. First, the first level hash function should be chosen randomly again until some conditions(Martin has the details) meet. So, the parameter used for expanding hash table is credential. It can save the frequency of rehashing. We choose to double the current amount of slots.

Compared to Cache-conscious hash table, the insertion running time is almost the same if the perfect hash table initially large enough. In term of querying runtime, perfect hash table is almost 3 times faster than cache-conscious hash table. (I use the same 1,000,000 random integers respectively).

3.8 Map

Map such as std::map is widely used in projects. It provides the convenience to get value by key. The performance of map becomes critical. std::map is not as fast as people want no matter insertion, looking up or serialization, especially for huge amount of data. We develop 2 kinds of hash tables to replace std::map respectively for string and integer of key type. The random test experiments show that our map's overall run-time performance is much better than std::map for large scale data set.

3.8.1 Cache-Conscious Integer Hash Table

It's an open address hash table. That says all entry records are stored in the bucket array itself. When a new entry has to be inserted, the buckets are examined, starting with the hashed-to slot and proceeding in some probe sequence, until an unoccupied slot is found. When searching for an entry, the buckets are scanned in the same sequence, until either the target record is found, or an unused array slot is found, which indicates that there is no such key in the table. The name "open addressing" refers to the fact that the location ("address") of the item is not determined by its hash value. (This method is also called closed hashing; it should not be confused with "open hashing" or "closed addressing" which usually mean separate chaining.)

Well known probe sequences include:

- linear probing in which the interval between probes is fixed (usually 1).
- quadratic probing in which the interval between probes increases by some constant (usually 1) after each probe.
- double hashing in which the interval between probes is computed by another hash function.

We adapt linear probing. If the data set is with in a cache line, this probing will be better choise. A drawback of all these open addressing schemes is that the number of stored entries cannot exceed the number of slots in the bucket array. In fact, even with good hash functions, their performance seriously degrades when the load factor grows beyond 0.7 or so. For many applications, these restriction mandate the use of dynamic resizing, with its attendant costs. In our application, when entry exceed the number of slots in the bucket array, we enlarge the bucket array. This indicates that user can insert as many data as they want when they are not aware of the size of bucket array.

For integer key type, we just adapt an integer array and linear probing for aspect of less cache miss. Value field is put into an std::vector. On the other hand, normal open addressing is a poor choice for large elements, since these elements fill entire cache lines (negating the cache advantage), and a large amount of space is wasted on large empty table slots. So, it's just for integers.

3.8.2 Cache-Conscious Collision Resolution String Hash Table

In-memory hash tables provide fast access to large numbers of strings, with less space overhead than sorted structures such as tries and binary trees. If chains are used for collision resolution, hash tables scale well, particularly if the pattern of access to the stored strings is skew. However, typical implementations of string hash tables, with lists of nodes, are not cache-efficient.

With the cost of a memory access in a current computer being some hundreds of CPU cycles, each cache miss potentially imposes a significant performance penalty. A cache-conscious algorithm has high locality of memory accesses, thereby exploiting system cache and making its behavior more predictable. There are two ways in which a program can be made more cache-conscious: by improving its temporal locality, where the program fetches the same pieces of memory multiple times; and by improving its spatial locality, where the memory accesses are to nearby addresses. Chains, although simple to implement, are known for their inefficient use of cache. As nodes are stored in random locations in memory, and the input sequence of hash table accesses is unpredictable, neither temporal nor spatial locality are high. Similar problems apply to all linked structures and randomly-accessed structures, including binary trees, skiplists, and large arrays accessed by binary search.

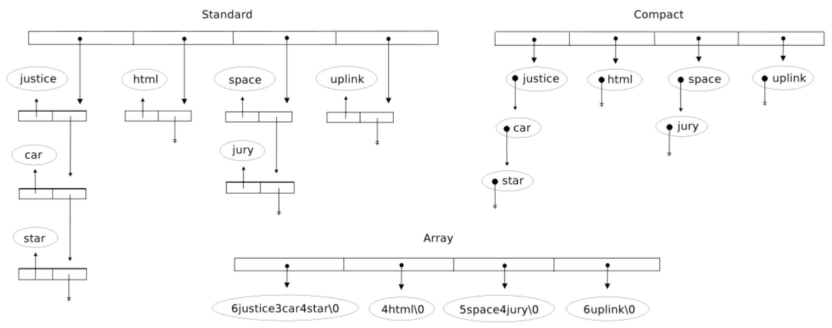


Figure 6: The standard-chain (left), compact-chain (right) and array (below) hash tables

This work is based on Nikolas Askitis and Justin Zobel's work. Every node access in a standard-chain hash table incurs two pointer traversals, one to reach the node and one to reach the string. As these are likely to be randomly located in memory, each access is likely to incur a cache miss. In this section we explain our proposals for eliminating these accesses. We assume that strings are sequences of 8-bit bytes, that a character such as null is available as a terminator, and a 32-bit CPU and memory address architecture. We propose a novel alternative to eliminate the chain altogether, and store the strings in a contiguous array. Prefetching schemes are highly effective with array-based structures, so this array hash table (shown, with the alternatives, in Figure 6) should maximize spatial access locality, providing a cache-conscious alternative to standard and compact chaining. Each array can be seen as a resizable bucket. The cost of access is a single pointer traversal, to fetch a bucket, which is then processed linearly. The experiment shows it's much faster than dynamic hash table which is one of the fastest linear hash proposed by Parson.

3.9 B-trie for disk-based string management

3.9.1 Basic trie

A trie, or prefix tree, is an ordered tree data structure that is used to store an associative array where the keys are usually strings. Unlike a binary search tree, no node in the tree stores the key associated with that node; instead, its position in the tree shows what key it is associated with. All the descendants of a node have a common prefix of the string associated with that node, and the root is associated with the empty string. Values are normally not associated with every node, only with leaves and some inner nodes that correspond to keys of interest. So, every inner node of trie has to maintain an alphabet of corresponding language. For Chinese, there are about three thousands characters usually used. That is to say every node will be thousands bytes, which is really bad for memory performance and running time. And the large memory usage become the main problem to trie.

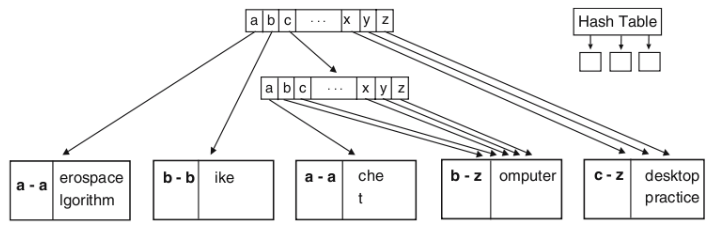
3.9.2 B-trie

The B-trie is an unbalanced multi-way disk-based trie structure, designed to sort and cluster strings that share common prefixes. It saves memory by put part of strings together into a bucket. The main components of our B-trie are as follows:

Trie nodes A trie node is an array of pointers, one pointer per character. Say, the ASCII table, there're 128 pointers in total. The prefix of a string is consumed by these nodes. Pointers in node point to other nodes or buckets.

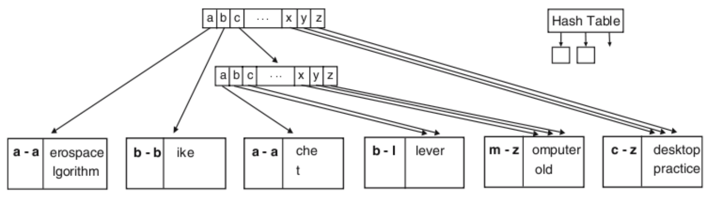
Buckets A leaf node of trie. A container stores strings after consumed by trie nodes. There're two kinds of bucket, pure bucket and hybrid bucket. Pure bucket stores strings which share the same first character. Hybrid bucket stores strings starting with different first characters.

Hash table Not every string inserted into trie is stored in it. Some relatively short strings are consumed by nodes and don't make it to leaf. Those strings will be stored in hash table.

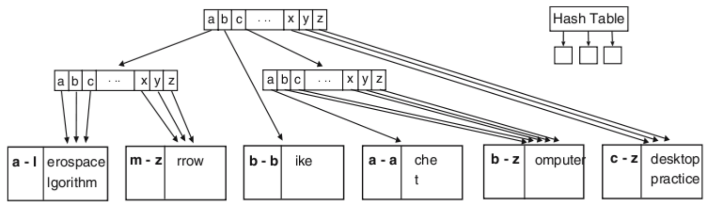


The words "cat","algorithm","computer", "practice", "cache", "bike", "desktop" and "aerospace" were inserted into the B-trie, creating three pure buckets (first three from the left) along with two hybrids.

The hash table stores strings that are consumed. "c" for example, would be consumed by the root trie and "a", would be consumed by the first pure bucket



The strings "cold" and "clever" were inserted into the B-trie in Fig. 3. The second hybrid bucket (from the right of Fig. 3) split, creating two new hybrids



The word 'arrow" was inserted into Fig. 3. The left-most pure bucket split into two hybrids and a new parent trie

Figure 7: B-trie insertion progress

It borrows the design of the burst trie to maintain a space-efficient trie, by storing strings within buckets that are structurally similar to those described for the B+-tree: fixed-sized disk blocks represented as arrays. Once a bucket becomes full, a splitting strategy is required that, in contrast to bursting, throttles the number of buckets and trie nodes created. The concept of a B-trie has been suggested by Szpan kowski. However, information about the data structure, such as algorithms to insert, delete, search, and how to split nodes efficiently on disk, is scarce.

3.9.3 Bucket splitting

The most important operation of B-tire is splitting. We propose that buckets undergo a new splitting procedure called a B-trie split. When a bucket is split, a character is first selected as a split-point and the strings are then distributed according to their leading character. That is, strings with a leading character smaller than or equal to the split-point remain in the original bucket, while others are moved into the new bucket. In this approach, the set of strings in each bucket is divided on the basis of the first character that follows the trie path that leads to the bucket. (Each node in the path consumes one character.)

When all the strings in a bucket have the same first character, this character can be removed from each string; subsequent splitting of this bucket will force the creation of a new parent trie. We label these buckets as pure. When the set of strings in a bucket have distinct first characters, several paths in the parent trie lead to it. We label these buckets as hybrid; subsequent splitting of this bucket will not create a new parent trie. Fig 7 illustrate examples of this splitting procedure.

In either case (hybrid or pure), each bucket is a cluster of strings with a shared prefix, a property with clear advantages for tasks such as range search. In addition, the B-trie offers other advantages. One is that the cost of traversing a chain of trie nodes can be, in comparison to the traversal of internal B-tree nodes, significantly lower; identification of a bucket involves no more than following a few pointers. Another is that short strings which are the commonest strings in applications such as vocabulary management are likely to be found without accessing a bucket and can be conveniently managed in memory. This splitting process is, however, a major contribution, as it solves the problem of efficiently maintaining a trie structure on disk for common string processing tasks. A potential drawback compared to a B+-tree, is that splitting a bucket cannot guarantee that the two new buckets are equally loaded. In most cases, the load is likely to be approximately equal. Another drawback is the applicability of bulk-loading. To bulk-load a data structure implies populating leaf nodes without consulting an index. This is accomplished by using sorted data; the index is constructed independently as the leaf nodes are sequentially populated. Bulk-loading is an efficient way of constructing B+ -trees. However, the B-trie cannot be efficiently bulk-loaded because its index which can consume strings is not independent from the data stored in buckets.

3.9.4 Implementation

For full usage of memory in B-trie, we adopt caches for fast memory access. Fig 8 shows the architecture of our implementation of B-trie. Except the data of tire node and bucket on disk, there're two caches for them respectively. So, the operation like insertion, updating etc. firstly will be executed in memory. If the required data doesn't exist in cache, then, it will be loaded from disk. The cache strategy is that latest and most frequently visited ones stay, and older and rarer visited ones out. We generate 1,000,000 random strings with length limits, and used these strings to test B-trie and B-tree. The tables below have detail.

Table above shows the experiment results by testing 1,000,000 random string with max length 20 and 200. The content of this table includes inserting running time, memory and disk consumption, and accumulative querying time for searching for those 1,000,000

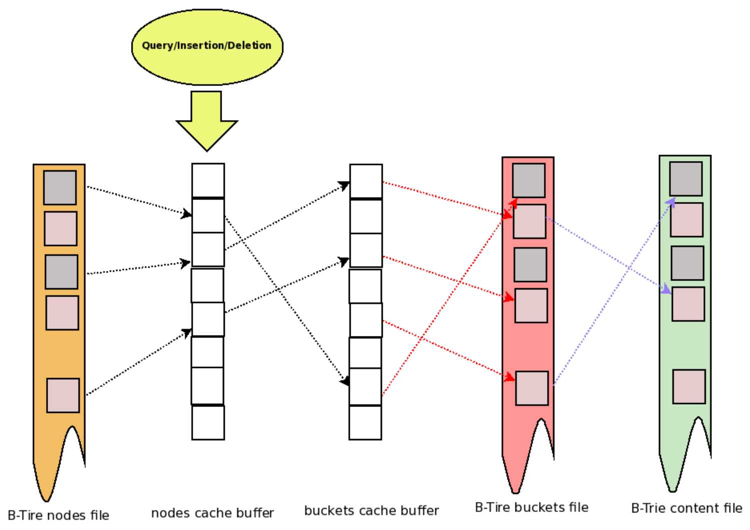


Figure 8: B-trie implementation architecture

Table 2: B-Trie performance with different bucket size to 1,000,000 random strings

Bucket size(byte)	**Str max len**	**Insertion(s)**	**Memory(MB)**	**Disk(MB)**	**Self-Query(s)**
2000	20	4.6	320	30.3	3.35
	200	7.96	519	202.4	4.66
8196	20	4.53	208	33.3	3.36
	200	5.76	381	141.1	4.61

strings, respectively, with different bucket size and max string length. The bucket size of this algorithm is credential.

Table 3: B-Tree performance to 1,000,000 random strings

Str max len	**Insertion(s)**	**Memory(MB)**	**Disk(MB)**	**Self-Query(s)**
20	6.78	-	-	-
200	10.02	-	300	-

According this above table of B-Tree's performance, B-trie has advantages comparing B-tree in some aspects while dealing with something like dictionary looking-up.

3.10 An external sort: AlphaSort

This work is based on Chris Nyberg's work "AlphaSort: A Cache-Sensitive Parallel External Sort" in 1995. A new sort algorithm, called AlphaSort, demonstrates that commodity processors and disks can handle commercial batch workloads. Using commodity processors, memory, and arrays of SCSI disks, AlphaSort runs the industry-standard sort benchmark in seven seconds. This beats the best published record on a 32-CPU 32-disk Hypercube by 8:1. On another benchmark, AlphaSort sorted more than a gigabyte in a minute.

AlphaSort is a cache-sensitive memory-intensive sort algorithm. We argue that modern architectures require algorithm designers to re-examine their use of the memory hierarchy. AlphaSort uses clustered data structures to get good cache locality. It uses file striping to get high disk bandwidth. It uses QuickSort to generate runs and uses replacement-selection to merge the runs. It uses shared memory multiprocessors to break the sort into subsort chores. Figure 9 shows the work flow of this algorithm.

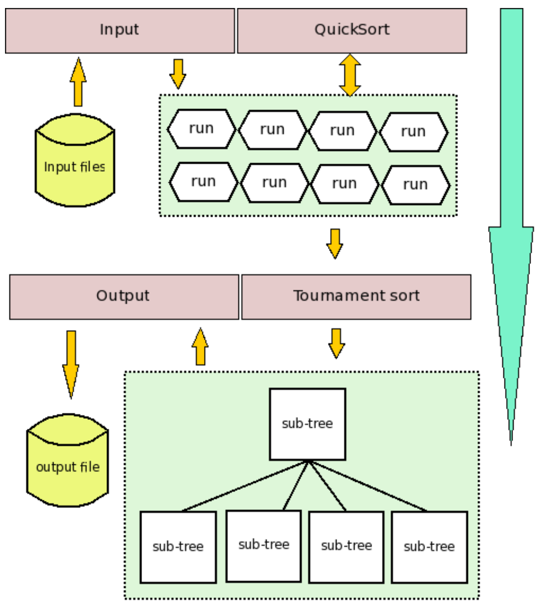


Figure 9: Work flow of AlphaSort

3.10.1 Input records

The records to be sorted have to include key field and content field. Content field follows the key field directly. No matter how long is the key field, we only use 4 bytes (user can define how many bytes) of the key as pre-key to compare each other. If two records have same pre-key, we use next 4 bytes to compare. Consequently, we may use part of record content to compare when the key is the same. That makes sense. In that way, we would not worry about the key type users may give. And the content of the records may be very long. It costs a lot to copy records while sorting. So, we only load pre-key into memory, and add record's file handler and address together as representative of a record.

3.10.2 Cache-sensitive quick-sort

We group inputs into small groups which can be hold in CPU cache. We call that small group a run. Records in one group can be sorted without cache miss. That means hundreds times promotion of run-time compared to in-memory-sort. Because of the limited memory, some sorted runs must be stored in some temporary file for the next step: merge to use.

3.10.3 Cache-sensitive tournament tree sort

After every run is sorted, a tournament tree should be built to merge runs. Tournament tree is kind of binary tree. parent node is the smaller/bigger one of child nodes. The root node is the smallest/biggest one in a tree. Initially, the first records of every runs are used to build the tree. So, the root is the smallest/biggest one of the all the records. And next record would be added into tree in place of the root record should come from the same run as the current root record does. The output node of this tree-sort is put into a buffer while output procedure is reading from this buffer and writing them into output file in disk.

In order to use cache efficiently, we split the binary tree into blocks whose size fit cache size. And one block represent a sub-tree. Within a block, we use array to store this sub-tree. So, there is no cache miss of any replacement-selection within one block. In term of replacement-selection within the entire tournament tree, there are only a few of cache miss when it switches between blocks.

3.10.4 Implementation

We randomly generate 1 million records of the entire size of 54Mb within one file. It needs about 4.5 seconds to get it sorted. And if we use multi-thread, it needs 6.5 seconds. It says that the switches between threads needs time and cause more cache miss. In term of one thread, it needs 0.5s to input, 1.0s to sort and almost 3.0s to output the results. Because, we do not load records' content in memory. We need to read the records' content in the input file into memory then write it into output file. The file seeking happens a lot when output. We try to use a file cache to improve it. The cache is used to pre-fetch the records from file while reading some records. It gets a good result while inputting, but costs more time while reading from input for output. Because, while inputting, records are read sequentially. But when output, records are read only once, and records location can't be predicted. So, the best idea for non-parallel disk is to use small and multiple files as input to save the file seeking time.

3.11 Trie Indexer

The main purpose of this access structure is to give frequency of any substring in a large corpus and which documents this substring belongs to. Another function of this structure is to give all the following terms of a given phrase. There're several choices for this job like suffix array and so on. Suffix array is an array of integers giving the starting positions of suffixes of a string in lexicographical order. The easiest way to construct a suffix array is to use an efficient comparison sort algorithm. This requires $O(nlogn)$ suffix comparisons, but a suffix comparison requires $O(n)$ time, so the overall runtime of this approach is $O(n^2logn)$. More sophisticated algorithms improve this to $O(nlogn)$ by exploiting the results of partial sorts to avoid redundant comparisons. In a large corpus, there may be gigas of substrings. Obviously, the array can't be holded entirely on memory. That will be a big problem for search. Otherwise, it involves merging the same strings together to get a frequency. Large amount of memory copying will happen a lot. For trie, it's constructed by edges and nodes, large percentages of edges and nodes can be reused in large amount of data, which reduces the space requirments a lot, and it's also easy to count the access frequency of nodes and get the following nodes of a given node. And the frequency of child nodes can be estimated on some level by the father node since frequency of child nodes must not be larger than father's. So, if we know frequency of some node is 1, it's not nessaray for us to go down to get the frequency of what we are looking for.

3.11.1 Trie Structure

Our trie is not exactly as traditional trie. In trie tree as what book said, every node is an alphabet. every entry in alphabet is a pointer to the following nodes. In that way, the space efficiency is a big problem. A big part of alphabet will be empty. And it's too large for each node.

Our trie tree is more like a table called trie table as Figure 10 shows. Every entry of table points to a node. Every node is a sorted vector by edges. Every edge is along with a table entry index which points the following node this edge leading to. Node frequency is stored as another vector according to the trie table. And there's a document list vector indicating the document list to specific node. That's why we call it indexer. There're some advantages to design it in that way compared to tree structure. In general, this structure is easy and lean, that's realy good for maintaining and easy to write and load to file. And it's more space efficient. For tree structure, along with the edge, there's a pointer to the next node, it takes 8 bytes to store it. But now, along with edge is a table entry index which just take 4 byte to store. That's fifty-percent saving. For large data set, that's very credential.

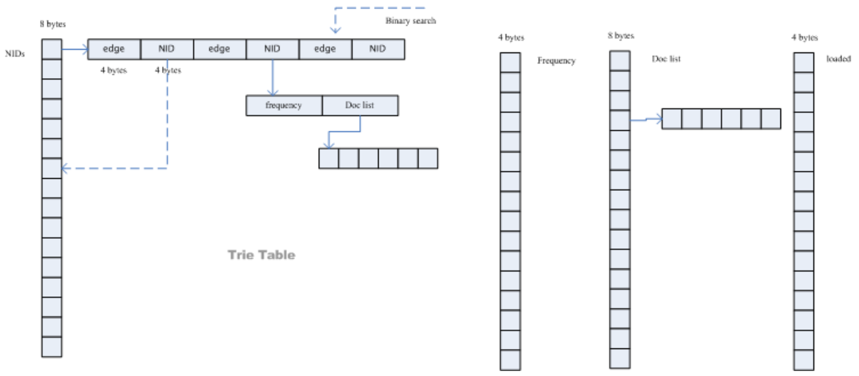


Figure 10: Trie table structure

To handle a large data set, data would be inserted into indexer part by part since the limitation of memory. And there're no involvement between every parts. How to do this? We sort this data set firstly. Our input is phrases, we sort it by their first term. Let's take an example. After we have inserted all the phrases starting with "A", all the tree paths start with "A" in root node will never be accessed, and we can put the entire subtree onto disk. That makes fast external construction of trie indexer upon a large data set possible.

3.11.2 Sort Algorithm

The sort algorithm is very credential to this algorithm. The first data, record position in file and length will be extracted from data set to be another structure called pre-key what is to be sorted actually. These pre-key will be distributed into several buckets. Quick sort is adopted to get bucket sorted. After every bucket has been sorted, merge them into one bucket. After getting a sorted pre-key queue, the next step is to generate a sorted data set according to the original one. After been sorted, the last record in original data set may become the first one. That involves random file access of the original data set. As we know, it's really a big problem for large data set. What we adopted is a file cache. Firstly, this file cache will load the fist part of original data set into memory. Go through the sorted pre-key queue, if the record address is within the cache, read it from cache and write it to the output file, otherwise, just seek to the next position in output file according the length of this record. After traversing the entire pre-key queue, load the next part of original file into file cache and so on until the entire original data set has been loaded once. In this way, all the access of data on file is sequential. This makes get large data set sort possible.

3.11.3 Indexing and Query

After all the phrases being sorted by the first term, the real indexing procedure is taking place. Here's a problem have to be solved, there're will be a lot of leaf nodes. Since the trie table entry can't be unloaded onto file during construction, if there're too much nodes, say a giga (possible for large data set), this algorithm will fail. And a big part of nodes are leaf node in which the table entry stores nothing. So, we eliminate leaf node in the trie table. But the leaf node also hold some important information like frequency and document list. We store them in another structure indicated by leaf node address in place of the table entry index along with edge. Another problem is how we distinguish this is table entry index or leaf node address. Though table entry can't exceed a giga, we add one giga to leaf node address. If this index is larger than one giga, it's a leaf node address. Another issue should be document list of node. Not every node has document list, only leaf node or once-to-be leaf node will hold document list. That's mainly for the consideration of space efficiency. Thus, when we want to get a document list of a given phrase, we must go down to all the following nodes and append them all together.

In terms of query, we partially load the trie table into memory. Since most nodes' frequency is 1, we don't need to load these node. As mentioned before, if we want to get frequency of "ABCD", and now we have found frequency of "AB" is 1, thus the frequency of "ABCD" is 0 or 1. Actually, frequency of 0 or 1 is meaningless to most usage. In that way, we only load nodes whose frequency is larger than one. For one-frequency nodes, we can load part of them if we have spare memory. Because, query for following terms of a given phrase happens.

3.11.4 Implementation Result

For a large corpus as 1M English Wikipedia documents, the phrases (we use punctuations and stop word to segment) need to be inserted are almost 54M including all the suffix. It needs half an hour to construct the trie table. In term of key word extraction algorithm, the entire process needs less than 3 hours upon this corpus.

4 Corpus Management

Corpus management component of AM-Lib provides storage services for IR-Lib. It is necessary because each component of IR-Lib will read data from corpus and output the results to a generic structs, therefore refactoring this common part into a single library will improve the system's reusage.

Existing project as *SML* provides similiar components as DocumentBag,etc. We can base corpus management on sml. What's more, IR-Lib needs a powerful matrix component to store the middle temporary computation outputs and the ultimate results.

4.1 Design of Matrix Library

Matrix is one of the most important fundamental component that is required by all kinds of machine learning and information retrieval algorithms. Besides the general numeric matrix utilities, we plan to include the following characteristics:

- A general matrix that has both memory and file version.

  File version is important because of the large scale data to be dealed with.

- SVD Decomposition, QR Decomposition, LU Decomposition, Eigenvalue Decomposition.

  These utilities are extremly useful in machine learning and information retrieval.

- Hessian matrix

  Hessian matrix is useful in Bayesian inference and decision theory.

Since the matrix library is required to be implemented with a modern generic design, what's more, a matrix library that provides general numeric utilities is itself a large work, therefore, we should base our implementation on the existing library, or else, the matrix library would have been a large engineering work. Taking the consideration of the file version matrix, together with the generic design, it means that the library that we choose to base on should be totally hacked, or else both of these two requirements could not be satisfied.

4.1.1 Boost.uBLAS

Boost.uBLAS provides templated C++ classes for dense, unit and sparse vectors, dense, identity, triangular, banded, symmetric, hermitian and sparse matrices. The storage design of *uBLAS* is based on *unbounded_array*, which adopts *std::allocator* to allocate and deallocate the memory of its internal elements, it is therefore means that although *uBLAS* provides an implementation of memory version only, we could replace *std::allocator* with our above referred persistent allocator to provide a file based matrix library very easily, for example:

```
#include <boost/numeric/ublas/matrix_sparse.hpp>
#include <boost/numeric/ublas/io.hpp>
#include <am/filemapper/persist.h>

int main () {
    using namespace boost::numeric::ublas;
    using namespace izenelib::am;
    //we assign a file to be used here
    map_file root("matrix.map",1, create_new|auto_grow, 1);
    compressed_matrix<double,row_major, 0,
            unbounded_array<std::size_t, izenelib::am::allocator<std::size_t> >,
            unbounded_array<double, izenelib::am::allocator<double> > > m (300, 300, 300 * 300);
    for (unsigned i = 0; i < m.size1 (); ++ i)
        for (unsigned j = 0; j < m.size2 (); ++ j)
            m (i, j) = 3 * i + j;
    std::cout << m << std::endl;
}
```

5 Components of IR-Lib

IR-Lib is a collection of algorithms in machine learning and information retrieval, together with the Corpus Management component of AM-Lib, it could provide a generic framework for search applications. Both machine learning and information retrieval have covered lots of fields, therefore, the main purpose of IR-Lib is to provide a scalable framework together with general algorithms, then in future, more advanced algorithms could be added easily.

The relationship between machine learning and information retrieval is very close and machine learning could be seen as the lower layer to provide methods for information retrieval's usage. Therefore IR-Lib could be composed of two layers. In addition, there exists some fields in information retrieval that has not adopted methods provided by machine learning, such as recommendation systems, preprocessing, etc. We will talk about all the components of IR-Lib one by one.

5.1 Duplication detection

Duplication detection is used for eliminating all the duplicated documents in result of query. Duplicated document means that they are different only from few words or format such as color. We define 2 documents as duplicated that they must have at least 90% similarity from content. And duplicated documents have transitive relationship. Document A is duplicated from document B, and document B is duplicated from document C. Then, it turns to that document A is duplicated from document C.

The direct way to detect duplication is to compare documents word by word, then, to compute the similarity of 2 documents. If the similarity rate exceeds a threshold, it's defined as duplicated. But for large scale documents database, say, 50 million documents there, the computation scale is unacceptable. The approach always adopted is to turn the content of documents into a series of bits called document's fingerprinting. It's like fingerprinting of human being, can be used to identify people. One document has one unique fingerprinting.

Document's fingerprinting is a certain length of bit string which can be generated by a few of ways like hash function, random projection and etc. The main work here doesn't focus on fingerprinting, so the detail would not be discussed here. Henzinger's paper 'Finding near-duplicate web pages: a large-scale evaluation of algorithm' has the detail.

The entire process of duplicate detection is composed of a few steps. We mainly discuss the data structures used and data flows here. Our purpose is to detect duplication among at most 50 million documents. If the fingerprinting is of 48 bytes length, it needs 2.4 GB. Every document has an identity, an 32 bit unsigned int. For 50 million documents, it needs 200 Mb. Any small extra information or data combined to each document will cost a lot space to store in total. During processing, a lot intermediate result of computation must be stored. Thus, to process as large as 50 million documents, all the data can't be stored just in memory obviously. We carefully designed a serial of data structures and flow of data to handle that large documents database. That is this section all about. The entire process is composed of like adding the documents, pre-clustering, indexing (pair-wise comparison) and query. We discussed it detailedly in following sections.

5.1.1 Adding documents

Adding documents have done 3 jobs. The document IDs are recorded into an array. The fingerprints of documents have been inserted into two kinds of data structure and stored onto disk for fatherly used by clustering respectively. There're 2 kinds of data structures used in this part. One is an file version hash table as Figure 11 shows. It is used for fast access the fingerprinting by a given index of document (It's mainly used when pair-wise comparison). It's composed of hash table part (docid is the key and addr is the value) and cache part. The 'docid' in this figure indicates the index of documents but not identity of document. Because the index of a document can indicate the location of its fingerprinting stored in file. The 'addr' indicates the location where the fingerprinting stored in cache. When do search, firstly find the 'docid' in hash table, as the 'addr' shows, find the corresponding fingerprinting in cache. If the 'docid' in cache is the same as what we are searching, just fetch the fingerprinting. Otherwise, fetch the fingerprinting from file into position of the oldest one and update hash table.

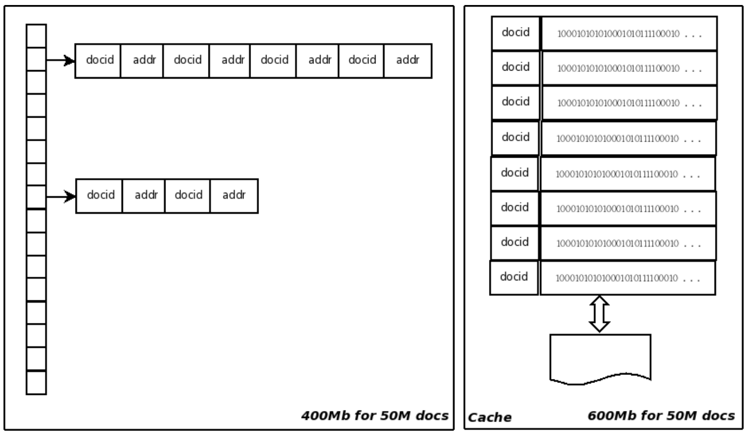


Figure 11: File version fingerprinting hash table.

The second data structure as Figure 12 shows. It's mainly for fast access of partial fingerprints of all documents, used by pre-clustering. As we know the total amount of fingerprints is very large that can't be holden into memory. And as pre-clustering needs, it

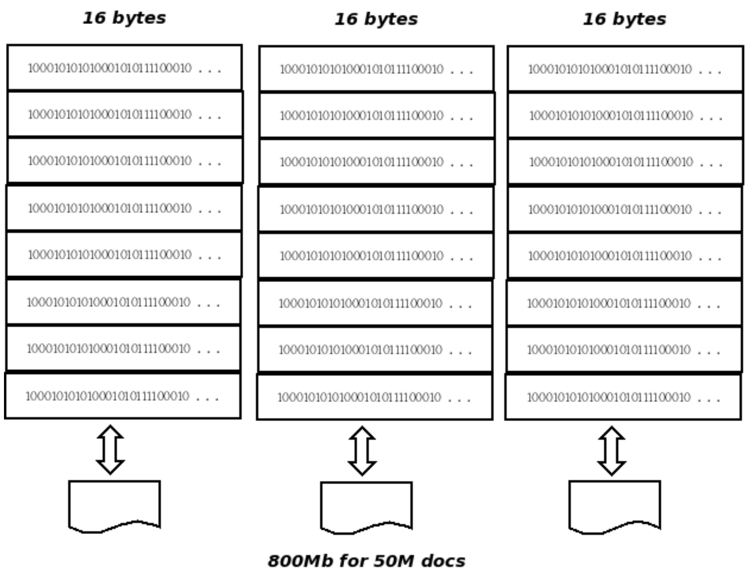


Figure 12: Partial fingerprinting of all documents.

hashes part of a document's fingerprinting. Thus, for 48 bytes fingerprinting, we can load it for 3 times (if pre-clustering just need to hash 1/3 fingerprinting) and take 50 million documents for example, we need 800 Mb memory for the entire pre-clustering process which reads from files for 3 time. To sum up, they're just 3 arrays. Every array holds 1/3 fingerprinting of all documents.

5.1.2 Pre-clustering

Since we can't do pair-wise comparison for large amount documents, it needs to take pre-clustering first to reduce the scope of pair-wise comparison. Some documents that we can easily identify they can never be in the same group will not do comparison ever. We split fingerprinting for, say, 3 parts. Thus, it needs 3 hash tables to store the result (as Figure 13 shows). If 2 documents has a same parts among these 3 parts, they can be possibly in the same group finally. On the contrary, if 2 documents have no same parts, for statical reason, it's really rear for these 2 documents duplicated. Data structure 12 is used for this step. Once it's loaded into memory, hash them into data structure showed as Figure 13.

5.1.3 Indexing

This is the most time-consuming part. It needs to use the result of pre-clustering and the file version hash table of fingerprinting to access the fingerprinting. And a group table (as Figure 14 show) will be generated. If a document has no duplicated document, it will not be in this table. The front part of the table is a hash table. It can fast find group ID which indicates all the group members. It iterates all the documents in 3 pre-clustering hash tables. Take one document as an example, it firstly find an candidate group in the first pre-clustering hash table, if the first DOC ID is the DOC ID we're processing (if it's not, that indicate we have processed this pre-clustered group), we do all the pair-wise comparison in this group. Then, look into the second pre-clustering hash table, as it goes on until all the pre-clustering hash tables have been searched for this document. If 2 documents are detected positively in this step, add them into group table. Then, we turn to next document.

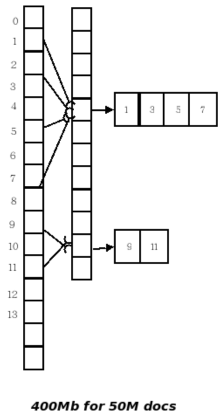


Figure 13: One of the pre-clustering hash table. Documents 1, 3, 5, 7 are clustered into one group.

We may discover that pre-clustering groups may have a lot in common and there must be a lot of duplicated comparison. So, we adopt prime numbers. We generated 50 million prime numbers ahead of duplication detection and stored in file. Now, we load them into memory and it takes about 200 Mb. Certainly, we can just load part of them as we need. One prime number is occupied by one document. And there's another array and the multiplication of 2 prime numbers which represent 2 documents will be stored in it, if 2 documents are compared. This multiplication result of a certain document records which documents have been compared with the certain document. So, before comparison, check if prime number of comparing document is a common divisor of the multiplication of both documents. That can easily prevent double comparison of documents. And this also can save a lot of time while incremental indexing documents.

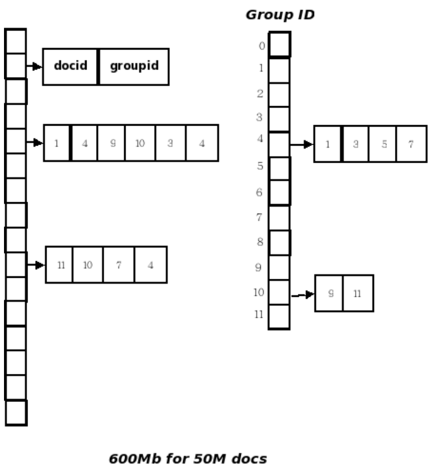


Figure 14: Group table. Documents 1, 3, 5, 7 are clustered into one group.

5.1.4 Query

Our main purpose of duplicate detection is to find duplicated documents of a given document. As what we get from previous steps, it's a group table. We have discussed it in the previous section. For the memory usage, other components can be unloaded into disk only leave group table for query. To find a group, it just needs one hash operation so that we can image how fast it can respond to an query.

6 Machine learning Components

- Supervised Learning.
  Wisenut-classifier has implemented most of the basic supervised learning methods. We plan to replace the interface to *SML* with the interface to new corpus management component of AM-Lib, and then refactor it to the generic design.
- Unsupervised Learning.
  Clustering-framework has already doen a good job of it. Therefore, the relavant job of this component is to make *Clustering-framework* suit for the whole framework of IR-Lib.
- Learning Complex Models.
  1. EM(Expectation—Maximization), which is also a basic learning approach in semi-supervised learning.
  2. Hidden Markov Models.
  3. Sampling method, including MCMC.
  4. Graphical Models, graphical models including following directions, each of which is under hot research, we are not sure whether it is possible to implement all of them, just try to do that.
     (a) Bayesian Network.
     (b) Markov Random Fields.
     (c) Conditional Random Fields.
- Dimensionality Reduction. We plan to implement PCA at first, more approaches could be done in future if possible.

In summary, machine learning are still under fast developing process, therefore only some basic directions would be included into this library, we hope a good design framework could be provided in order that more learning approaches could be included into this library easily in future.

7 Information Retrieval Components

- Text Pre-Processing
  Text pre-processing techniques are mature and have been implemented by existing projects, therefore we can refactor them from existing code.
  1. Stopword Removal
  2. Stemming
  3. TF-IDF
  4. Tokenization
  5. Feature Selection
  6. Duplicate Detection

- Language Models
  It is necessary to refactor and integrate Jinglei's work into the library.
- Topic Modeling
  Topic modelling is a hot research direction and lots of new approaches appear continuously. We only plan to provide some topic modelling methods including LSI, LDA and 4-level PAM. We hope more topic modeling approaches could be easily added to this library.

8 Utility components

8.1 iZeneLib Log

Part of making them easier to develop/maintain is to do logging. Logging allows you to later see what happened in your application. It can be a great help when debugging and/or testing it. The great thing about logging is that you can use it on systems in production and/or in use - if an error occurs, by examining the log, you can get a picture of where the problem is. Good logging is mandatory in support projects, you simply can't live without it. Used properly, logging is a very powerful tool. Besides aiding debugging/ testing, it can also show you how your application is used (which modules, etc.), how time-consuming certain parts of your program are, how much bandwidth your application consumes, etc. - it's up to you how much information you log, and where.Here, we describe what this log can do and how to use the izenelib log. This log is based on boost logging. So, you can use it coupled with boost logging. Let's see an example as follow.

```
18:59.24 [dbg] this is so cool
18:59.24 [dbg] this is so cool again
18:59.24 [app] hello, world
18:59.24 [app] good to be back ;)
18:59.24 [err] it's an error here
```

Level There're three levels, debug/application/error infomation. Their formats are just like above. You can use some maroc like follow to output three different infomation. If you want to disable any kind of log informatin, just define some switch like DBG_DISABLE/ APP_DISABLE/ ERR_DISABLE.

```
LDBG_≪"Output debug information!";
LERR_≪"Output error information!";
LAPP_≪"Output application information!";
```

Tags The defualt tags for three different information is just like [dbg]/[app]/[err]. If you don't like them, you can define them. Respectively, you can define DBG_TAG/ APP_TAG/ ERR_TAG to specify the tags.

Destination As defualt, all the three kind information will be ouputed into three files, "'dbg.txt"/ "'app.txt"/ "'err.txt". The file names are defined by DBG_LOG_NAME/ APP_LOG_NAME/ ERR_LOG_NAME. Of course, you can output all the information into one file. All of thoes information will not be printed onto console. If you want to do it, you just need to define some switchs as DBG2CONSOLE/ APP2CONSOLE/ ERR2CONSOLE.

Conditional log Sometime, you want to log according some condition while the program is running. You can do it like :

IF_DLOG(i%10==0)≪"i mod 10 is 0!";

It's outputed as debug information. You can use other kind of log with *IF_ALOG()/ IF_ELOG()*.

Initialize log This is a kind of globle log within one program. You just need to initialize it at the beginning of your main CPP file like this: ***USING_IZENE_LOG();***. Every time when you need to use log, don't forget to include the head file "util/log.h".

8.2 iZeneLib String

Programming languages generally provide a "string" or "text" type to allow manipulation of sequences of characters. This type is usually of crucial importance, since it is normally mentioned in most interfaces between system components and also is widly used in our projects. We usually use std::string or ylib::string which is a sub class of std::string. But std::string is not perfect and doesn't perform well in all circumstance. For example, if string goes very long, it's very time consuming by insertion and appending operations.

First problem is memory fragment and small-object memory wast. In project, strings are always not long and frequently constructed and destructed. And system calls like malloc and free are not designed for small objects. There is a big part of memory management information that combined with small objects. The utilization ratio is very low. And frequent construction and deconstruction using malloc/free is fragments generating. Functions like malloc/free are not well designed for this.

The consistency of interface of std::string with other STL components are bad. Take function 'find' for example. All other STL containers have the same type function. String is better to keep that consistency. And by STL design concepts, algorithms and structures are separated. An string methods set independent with types of strings self is highly needed.

For high run-time performance, STL adapts copy-on-write mechanism everywhere, and in std::string too. Copy-on-write is very efficiency improving technology indeed, but it's not suitable in all context. Like in multi-thread and rarely-copy-between-objects context, it will spend much time for lock/unlock and will be easy to generate bugs. So, let copy-on-write property be selective is necessary.

Another problem is CJK supporting. For much corpus, it's encoded by various encoding types. But, std::string only takes 1 byte as a character. And there's a lack of methods for transformation between encoding types.

We develop three kinds strings: vector string, deque string and tree string. They are designed for different usages. And they all use hlmalloc for the memory management, whose run time and fragment ratio is all lower than system call: malloc/free. There's an algorithm set where a lot of useful string methods are added in, are almost suitable for all the three types string. Copy-on-write technology is still adapted, but we let it selective. Almost all the characters in corpus are belonged to BMP in Unicode. That's to say only 2 bytes are needed to store characters in Unicode. Our string can deal with 2 bytes characters. And encoding types transformation methods will be in string methods set. Thus, we can transform text into Unicode, which is of various encoding types, before being processed.

8.2.1 Vector String

Actually, std::string is organized as vector. The advantages of our vector string is that we let copy-on-write selective and let user can change the growth rate when string needs to enlarge. Copy-on-write technology is widely used in hardware and software design. It prevents needless copy. There's an example. As C++ code below, these variables "a" and "b" all have the same memory address of their buffer. There's no copy operation between "a" and "b" till "b" is changed.

```
std::string a = "abcd";
std::string b = a;
```

For using copy-on-write technology, there must be some reference counter to decide whether it needs to copy into another new buffer or not. Like std::string we use the first byte of string's buffer to record the reference count. Thus, every object share the same buffer can see it. Vector string is just for those which doesn't need to be modified very much and not very long. If string is very long and modified frequently, we recommend to use strings in following sections.

8.2.2 Deque String

Deque is a double ends queue. Its advantages is for insertion from front and back. Middle insertion is also fast if at the right position and length. Deque string is not as vector string. There's an entry vector storing address to the bucket. And characters are only stored in buckets, and reference counter is at the first byte of entry like figure 15.

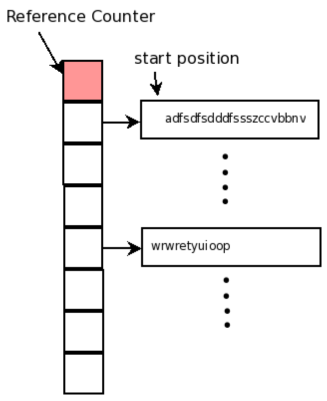


Figure 15: Deque string structrue

The traversal is slower than vector string. That's because it needs seeking address twice. But in this deque string, his iterator is faster than using operator [ ] to traverse, since iterator records last accessed position. The advantages for deque string is obvious, that appending at front or back will be much faster than vector string especially when string is very long. If your strings are very long and always being appended, deque string is highly recommended.

8.2.3 Balanced Binary Tree String

Balanced binary tree is for binary search and good extendibility. For frequently concatenated or inserted very long strings, tree structure is a good choice. We can call this string "rope" or "heavy weight" string. Ropes can be viewed as search trees that are indexed by position like figure 16. If each vertex contains the length of the string represented by the subtree, then minimal modifications of the search tree algorithms yield the following operations on ropes:

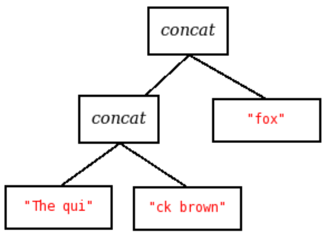


Figure 16: Rope representation of The quick brown fox

- Fetch ith character. A simple search tree look-up. Rather than examining the subtree containing the right key, we examine the tree containing the proper position, as determined by the length fields.
- Concatenate two ropes. Search tree for the position of concatenation.
- Substring. Two search tree split operations. We can take it as splitting two concatenated tree.
- Iterate over each character. Left-to-right tree traversal.

The first three of the above operations can be performed in a time logarithmic in the length of the argument, using, for example, B-trees or AVL trees. Note that since strings are immutable, any nodes that would be modified in the standard version of the algorithm, as well as their ancestors, are copied. Only logarithmically many nodes need be copied.

The last can be performed in linear time for essentially any search tree variant. Thus both concatenation and substring operations (other than for very short substrings) are asymptotically faster than for conventional flat strings. The last exhibits roughly the same performance. The first is somewhat slower, but usually infrequent.

There're problems comes. After string concatenation or insertion, tree rebalancing is needed. That needs to traverse all the vertex and shift their positions and is very complex. Here's an alternative way to simulate this balanced binary tree as figure 17. Here's a vector

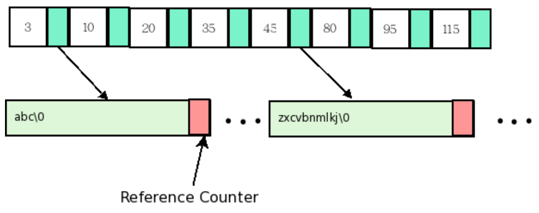


Figure 17: An improved balanced binary tree string

and some buckets. String characters are stored in buckets. The element of vector stands for the sum of length of buckets ahead and a pointer pointing to corresponding bucket. In terms of uniform access, it only needs a binary search for that vector to find corresponding bucket. It is equal to balanced tree search. In terms of insertion or concatenation, it doesn't need to be rebalanced anything, just need to shift elements' positions and add length sum in vector. Since the vector would not be large, this is time efficient. And the reference counter is stored in each bucket, so, when the content of bucket is modified, only some involved buckets need to be copied.

8.2.4 Experiment Results

This experiment is to do run-time performance comparisons of some crucial functions of strings like append, insert, substr and iterators. Since the structure particularity of various string, their strong points and weakness are not the same. The experiment's result could be a reference of trade-off when user try to use them.

There're 2 parts in this test. The first one is for some crucial operations, see Table 4 and the second is for iteration, see Table 5. The data for the first one are strings of 1k length. The run-time is counted by seconds and it's the sum of run time of operation which has took place for 100k times. The data for the first one are strings of 100k length. The run-time is counted by seconds and it's the sum of being transversed for 100k times. And there're 2 situations for the second test respectively for constant and mutable string, since uniform access run time of constant and mutable strings are not the same. In tables below, "-" means that some strings do not have that operations, "NAN" means that the run time is out of acceptation. And all the tests are taking place using "copy on write". And all the bucket size is set to 1k bytes if it's needed.

Table 4: Comparison of run-time performance of strings' operations

Operation	**std(s)**	**vector(s)**	**deque(s)**	**bbt(s)**
push front	-	-	13.10	11.88
append	0.2	0.07	0.52	0.01
substr	0.98	0.00	0.00	0.09
insert	NAN	NAN	NAN	19.27

As Table 4 shows, in term of insertion, bbt string is the best one. Other strings are not suitable for that operation. In term of pushing front, bbt string is also the fastest and deque is the second, but deque is more memory-saving. In term of appending, bbt is the fastest, deque is more memory-saving than others. Vector also is very fast, but vector and std string are too much waste of memory. std::string has 34% memory in waste. Vector has 38% waste of memory. All the substr are very fast.

Table 5: Comparison of run-time performance of strings' iterator

	operation	**std(s)**	**vector(s)**	**deque(s)**	**bbt(s)**
const	iterator	0.00	0.00	26.13	30.32
	operator[]	0.00	0.00	8.67	172.1
mutable	iterator	12.98	0.00	26.14	30.32
	operator[]	8.64	8.63	8.64	174.10

In Table 5, uniform access for constant strings are generally faster than mutable strings. That's because of "copy on write". And for long string types, deque's uniform access is much faster than bbt in constant or mutable string. For mutable string types, std string's iterator is much slower than vector string while operator [ ] of vector string is slower than str string's. So, for short type string, we recommend vector string. For long string, we recommend bbt string.

9 Appendix

Table 6: Implement schedule

	Miles-tone	**Start**	**Finish**	**In Charge**	**Description**	**Status**
1	Preparation for *iZENELib*	2008-11-01	2008-12-05	Yingfeng, Kevin	Study the generic design idea, refactor *YLib*,find solutions for important utilities including matrix, file block manager.	Finished
2	AM Interface Definition	2008-12-08	2008-12-12	Yingfeng, Peisheng, Kevin	Make sure the policy based AM interface	Finished
3	Encapsulation for basic AM methods	2008-11-01	2009-02-31	Kevin,	Encapsulate Linear hash table memory version, skip list memory version, etc.	Memory versions done
				Peisheng	Encapsulate sequencial DB, B-tree, skip list file version, etc.	Btree and SDB based on izenelib are finished and their efficiecy doen't decline.
				Liang	Encapsulate Priority Queue, etc.	In progress
				Vernkin	Encapsulate Perfect hash, etc.	In progress
				Kevin	File version of Trie, B-Trie for std::string and sfilib::UString	Done
				Kevin	Cache-conscious collision resolution string hash table, faster than linear hash table	Done
4	Storage manager	2008-12-08	2008-12-24	Yingfeng	An extremely efficient memory allocator together with a file block allocator should be provided,the former could improve memory version of AM methods remarkably and the latter could support file based data structure with high scalability and high performance	Finished
5	Matrix library	2008-12-25	2009-01-14	Yingfeng	An efficient matrix library is provided	Todo
6	Basic IR Library	2009-01-14	2009-01-31	Yingfeng	Basic IR-Lib could be provided, including corpus management, basic supervised and unsupervised learning	Todo
7	Pre-Processing	2009-01-01	2009-01-15	Kevin	Text pre-processing component is encapsulated.	Todo
8	Complex machine learning	2009-02-01	2009-02-28	Yingfeng	Learning methods for complex models have been added.	Todo
9	Network Library	2009-03-01	2009-03-31	Yingfeng	Distributed computing component is added.	Todo