Terminology:	Description:
$k = n_results$	/*number of results to displace*/
$m = n\_documents$	/*number of documents we have*/
n = n_query	/*number of query words*/
p= aver length of doculists	/*average length of document list*/
log(x)	/*log with base = 2 of value = x*/

Complexity of siftup(), siftdown(), heap\_insert(), heap\_overwrite\_head() and heap\_remove\_min()

The number of steps required for the function above is related to the while loop in siftup() and siftdown(). And the maximum number that the **While** loop has iterated equals the height of the heap. // heap.height is 1 based

h.height = while(heap.max > 0) {count(heap.max / 2)} = times of heap.max can be divided by 2 before getting a 0 i.e. heap.max =  $2^{\text{heap.heaight}} - 1$  // 1 for root is odd

 $\rightarrow$  heap.height = log(heap.max+1)  $\approx$  log(heap.max)

: complexity of these function  $\in$  O(heap.height)= O(log(heap.max))

Complexity of swap(), cmp(), min\_child(), new\_heap(), heap\_peek\_min(), heap\_peek\_key(), free\_heap(), insert\_at\_end() and get\_heap\_size(); print\_heap()

As these only have **If** statement and several constant variable assignment, All of these operations e(1)

In print\_heap(), just print heap's size times. it  $\in$  O(h.cur\_size)

# query.c task1

For function **initialize\_float\_array**(), it just sets an array of float to 0.0. So its time complexity  $\subseteq \Theta(m)$  as the size of the array is O(m)

For function **traverse\_document\_list()**, it sums score for each document in doculist[] by a **While** loop traverse doculists in a **For** loop. So its time complexity  $\in \mathcal{O}(np)$ 

For function **insert\_into\_heap()**, it uses **heap\_insert()** when heap is not full **heap\_overwrite\_head()** when heap is full and a bigger record is found. So its time complexity  $\subseteq O(\log(\text{heap.max}))$ .

For function topk(), it traverse from document id = 0 to m and try to insert them into the heap of result. So it does  $insert_into_heap()$  in a For loop m times in worst case. So its time  $complexity \subseteq O(mlog(heap.max))$ 

For function  $rec_print_heap()$ , it does heap\_peek\_min() at most k times then print heap linearly. So its time complexity  $\subseteq O(k\log(k) + k) \subseteq O(k\log(k))$ 

<pre>print_array_results(Index *index,</pre>	
k, m)	
SET score_arr[m]	∈ Θ(1)
topk_h←min-heap with h.max= k	€ 0(1)
$score\_arr[] \leftarrow 0.0$	€ O(m)
sum score foreach document	$\in \Theta(np)$
select topk scored document	$\in O(mlog(k))$

print result	€O(k log(k))
<pre>free_heap(priority_queue)</pre>	∈ Θ(1)
	$\in$ O(np + mlog(k) + k log(k))

### query.c task2

For function **initialize\_id\_heap**(), it inserts n non-0.0 {score:id} from doculists->head. So its time complexity  $\subseteq O(n \log(n))$ 

For function **multi\_way\_merge\_topk**(), 2 **While** loops stop when the we have processed all record in doculists. And we access id\_heap every loop, push into final result heap with max m times in outer loop. So its time complexity  $\in O(np * log(n) + m * log(k))$ 

```
print_merge_results(Index *index, k)
priority queue ← heap with heap.max=k
                                                \in \Theta(1)
id heap ← heap with heap.max=n
                                                \in \Theta(1)
tmp \leftarrow index->doclists
                                                \in \Theta(1)
insert n tmp's head data into id_heap
                                                \in O(n\log(n))
sum score for each document and select
                                                \in O(nplog(n)+
       topk scored document
                                                mlog(k))
                                                \in O(k \log(k))
print topk selected document
free(id_heap, priority_queue)
                                                \in \Theta(1)
                                                \in O(mlog(k)
                                                nplog(n) + k log(k)
```

#### Time Complexity of task1 and task2 analysis

worst case analysis

cost of print\_array\_results()

= O(np + mlog(k) + k log(k))

cost of print\_merge\_results()

= O(mlog(k) + nplog(n) + k log(k))

average case analysis

 $cost\ of\ \textbf{print\_array\_results}()$ 

foot note is not power!!!

 $= O(np + mlog(k)^1 + k log(k))$ 

 $= O(m + np + klog(k)log(m)), \text{ if } k <<^2 m = O(m+np)$ 

cost of print\_merge\_results()

 $= O(mlog(k)^3 + nplog(n) + k log(k))$ 

= O(m + klog(k)log(m) + nplog(n)), if  $k \ll m = O(m + nplog(n))$ 

Space Complexity of task1 and task2 analysis

space of **print\_array\_results**() space of **print\_merge\_results**() = O(array) + O(prioroty queue) = O(m+k) space of **print\_merge\_results**()  $= O(id\_heap) + O(priority queue)$  = O(n+k)

Task 1&2 in realistic

<sup>1 &</sup>quot;Then the expected number of update steps in total is under k.log n, and each update is O(log

k) – and in practice will be 1 or 2 steps. Thus the expected total number of operations is n + 1

k.log k.log n. The worst case is n.log k, for example when the items are in ascending sort order."

from  $w3lec2 \ slide6 \ O(mlog(k)) = O(m + klog(k)log(m))$ 

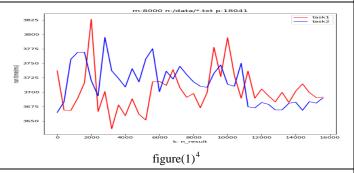
<sup>2 &</sup>lt;<: much smaller

<sup>3</sup> simillar as 1

Typically, p will not bigger than m. So  $p \le m$ . And the top scored result we want is always smaller than m. So, k << m. And n is smaller than m in common sense. (e.g. search engine like Google has limited query) Both tasks are dominant by O(m) in worst case if n << m. In the use of space, as n < m, Task 2 requires smaller space demand than task1. Therefore, Task2 has a better performance than task1 in realistic problem. For these two algorithms, they are more sensitive to the change in m and p than n and k. Because m is much larger than the other two in real problem.

#### Analysis of changes in k: n\_results

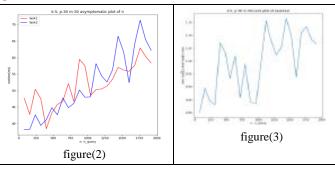
In this case, m, p and n are set to be constant, k is variable. Both tasks are dominant by O(klogk), which means they will have similar time consumption when k is quite large about k=10000. So task2 and task1 have similar time consumption when k grows.



figure(1) is plot for k in range(16000) shows task1 and task2 has different runtime initially. But eventually, they have a trend to have similar runtime as shown in graph. So the analysis above about k is supported by this graph.

# Analysis of changes in n: n\_queries

In this case, m, p and k are set to be constant, n is variable. On average, task1's complexity is dominant by  $O(np) \in O(n)$  as  $n \to \infty$ . And task2's complexity is dominant by  $O(nplog(n)) \in O(nlog(n))$  as  $n \to \infty$ . So task2 consumes more time than task1 in the long run as n grows to  $\infty$ .

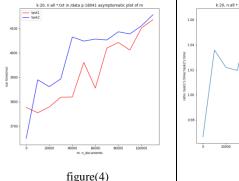


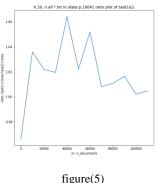
figure(2) shows task2 will requires more time than task1 as n increases in range(2000) excluding print\_heap(). figure(3) shows in practical, task1 runs 5%-10% faster than task2 as n >> m around n=1000 as it is a plot about task2 runtime/ task1 runtime. And the rate is increasing which illustrated in the analysis above.

### Analysis of changes in m:max number of documents

In this case, n, p and k are set to be constant, m is variable. On

average, both task1 and task2 is dominant by O(m) as  $m \rightarrow \infty$ . As a conclusion, task1 and task2 will have a similar time consumption, when m grows quite large.

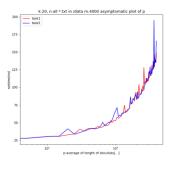




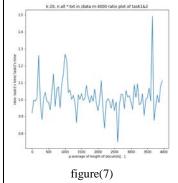
figure(4) is plot for m in range(1000000) including runtime of print\_heap(). Which shows when m is dominant, two algorithms have similar time consuming about m=80000. And figure(5) shows the ratio between two algorithm's running time approaches to each other as m  $\rightarrow \infty$ . And two algorithms' runtime has a linear growth determined by O(m).

### Analysis of changes in p: average length of doculist[]

In this case, n, m and k are set to be constant, p is variable. On average, both task1 and task2 has  $p \le m$ . When  $p \to m$ , task1  $\in$  O(m+np)=O(p) and task2  $\in$  O(m+nolog(n))=O(p). As a conclusion, task1 and task2 will have a similar time consumption, as  $p \to m$ .



figure(6)



figure(6) plots p in range(4000) excluding print\_heap() and shows task1 and task2's runtime approaches to each other as  $p \rightarrow m$  about p=2500. figure(7) shows the ratio becomes stable when we exclude outlier as p grows. These 2 figs show the analysis of O(p).

# Conclusion

As discussed in average analysis, although task2 requires more time consumption than task1 as n grows. But it is just a smaller factor of O(log(n)) in time consumption And task1 and task2 have a huge difference in memory space demand. On average, when n is not so close to m, task2 will require a slightly longer time to get the same result as task1 but require a smaller memory demand.

Task2 is preferred than task1 when n<<m for people who have normal search eager to get their results as soon as possible. Task1 is more preferred than task2 when people who have a huge huge amount of data than our daily query requirement want a shorter query time.

<sup>4</sup> every point is iterated  $3\sim4$  times and yaxis of plot is runtime or ratio, xaxis is parameter.