CS 325 Group Assignment 1

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1 Algorithm Description and Proof of Correctness

Our algorithm can be described as a divide and conquer algorithm, because we divide our problem size in half every time we recur. Let $D = [d_0, d_1, \cdots, d_{n-1}]$ be the array of delegates, where d_i is the party that the delegate at index i belongs to. If our array is longer than 1, we choose the midpoint of our array, $m = \lfloor \frac{n-1}{2} \rfloor$, and then think of our problem as two sub-arrays,

$$A = [d_0, \cdots, d_m]$$
 $B = [d_{m+1}, \cdots, d_{n-1}]$

We know that the majority party must have m+1 delegates (assuming we do truncated integer division when computing m). By the pigeonhole principle, we must have more that $\frac{m+1}{2}$ delegates of our majority party in either A or B, meaning that the majority party of D will also be the majority party of A or B, or of both A and B.

Case 1: Our majority party dominates A or B, not both Let $\operatorname{maj}(D)$ be the majority party element of D. Then either $\operatorname{maj}(D) = \operatorname{maj}(A)$ or $\operatorname{maj}(D) = \operatorname{maj}(B)$. By recursion we can assume that the majority size and element of A and B are both known. We use a count function to count the number of occurrences of $\operatorname{maj}(B)$ in A, and the number of occurrences of $\operatorname{maj}(A)$ in B. This will call the same_party() function m+m=n times total. Then we compare the count of $\operatorname{maj}(A)$ in D, to the count of $\operatorname{maj}(B)$ in D. Whichever is larger, we take to be the size of our majority party in D, and we know also which party is our majority.

Case 2: Our majority party dominates A and B In this case we check that maj(A) = maj(b), calling $same_party()$ once and simply combine the size of the majority in each.

When the size of our array is 1, we know that maj(D) is going to be d_0 , and that the size of the majority party is 1. This will be our base case for recursion.

2 Running Time Analysis

We can check the condition for the base case in constant time with a simple if statement, which starts us at O(1) complexity. To get the information for our sub-arrays A and B, we make 2 recursive calls to our function with an input size of $\frac{n}{2}$. We will work to compute the cost of this further on. Assuming that we have the majority party, and its size for A and B, we make one call to $\mathtt{same_party}()$ to check if we have $\boxed{\mathtt{Case 1}}$ or $\boxed{\mathtt{Case 2}}$. This check is constant time, meaning excluding the recursive step, we still have O(1) time complexity. Since $\boxed{\mathtt{Case 2}}$ is constant time, our worst case scenario is one in which we have $\boxed{\mathtt{Case 1}}$ each step of the way. Assuming that we have $\boxed{\mathtt{Case 1}}$, we must call $\boxed{\mathtt{same_party}()}$ n times, as in our algorithm description. This means that our function will operate in linear time, O(n), excluding the recursion.

To account for recursion, we must add $T(\frac{n}{2})$ to our running time twice, since we recur on both halves. This gives us $T(n) = O(n) + T(\frac{n}{2}) + T(\frac{n}{2}) = O(n) + 2T(\frac{n}{2})$. This will continue to branch out until $\frac{n}{2^i} = 1$. This will finally result in the following sum:

$$T(n) = O(n) + 2O\left(\frac{n}{2}\right) + 2^2O\left(\frac{n}{2^2}\right) + 2^3O\left(\frac{n}{2^3}\right) + \dots + 2^{\log_2(n)}O\left(\frac{n}{2^{\log_2(n)}}\right)$$

$$= O(n) + O(n) + O(n) + \dots + O(n)$$

$$= \log(n) O(n)$$

$$= O(n \log(n))$$