## More Algorithm Analysis

Computer Science Department University of Central Florida

COP 3502 - Computer Science I

## Announcements

- Comment on Class Workload thus far:
- \# of hours expected of a full-time college student:
- Just like a full-time job: around 40 or 50 or so hours/week
- It is said that for every hour in class,
- You can expect up to three hours of work outside class
- Now do the math:
- If you are registered for 12 credits
- That adds up to 36 hours of outside-class work per week
- For a total of 48 hours per week
- Now ask yourself:
- For this class, do you really put in 9 hours/week outside of the class?


## Announcements

## Comment on Class Workload thus far:

- Now ask yourself:
- For this class, do you really put in 9 hours/week outside of the class?
- Not even close!
- If there's no program due, the average student puts in ZERO hours per week outside class
- They don't even review notes for a MINUTE!
- So how long then does a program take?
- Let's even say 10 hours (which is high for most students)
- Since they are due every two weeks (or so)
- That adds up to 5 hours per week that you invest (at a max)
- Leaving still 4 hours per week of study time!


## Program 3

- Program 3: Match-Making
- Given a list of $n$ men and $n$ women
- Also given the men's ratings of the women
- And the women's ratings of the men
- Find the best overall matching of men and women in the group
- So you must find ALL possible matchings


## Program 3

- Program 3: Match-Making
- Example:

How many matchings will there be?

- Following chart shows how the men rate the women:

|  | Diana | Ellen | Fran |
| :--- | :--- | :--- | :--- |
| Adam | 4 | 8 | 7 |
| Bob | 6 | 7 | 5 |
| Carl | 5 | 9 | 6 |

- Following chart shows how the women rate the men:

|  | Adam | Bob | Carl |
| :--- | :--- | :--- | :--- |
| Diana | 7 | 6 | 8 |
| Ellen | 6 | 5 | 9 |
| Fran | 4 | 7 | 3 |

## Program 3

- Program 3: Match-Making
- Example:
- Here are the six (ALL) matchings:

| M1 | $\underline{\mathbf{S}}$ | M2 | $\underline{\mathbf{S}}$ | M3 | $\underline{\mathbf{S}}$ |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Adam+Diana | 4 | Adam+Diana | 4 | Adam+Ellen | 6 |
| Bob+Ellen | 5 | Bob+Fran | 5 | Bob+Diana | 6 |
| Carl+Fran | 3 | Carl+Ellen | 9 | Carl+Fran | 3 |
| Total | 12 |  | 18 |  | 15 |


| M4 | S | M5 | $\underline{\mathbf{S}}$ | M6 | $\underline{\mathbf{S}}$ |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Adam+Ellen | 6 | Adam+Fran | 4 | Adam+Fran | 4 |
| Bob+Fran | 5 | Bob+Diana | 6 | Bob+Ellen | 5 |
| Carl+Diana | 5 | Carl+Ellen | 9 | Carl+Diana | 5 |
| Total | 16 |  | 19 |  | 14 |

## Program 3

- Program 3: Match-Making
- Example:

This is clearly the best match!

- Here are the six (ALL) matchings:

| M1 | $\underline{\mathbf{S}}$ | M2 | $\underline{\mathbf{S}}$ | M3 | $\underline{\mathbf{S}}$ |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Adam+Diana | 4 | Adam+Diana | 4 | Adam+Ellen | 6 |
| Bob+Ellen | 5 | Bob+Fran | 5 | Bob+Diana | 6 |
| Carl+Fran | 3 | Carl+Ellen | 9 | Carl+Fran | 3 |
| Total | 12 |  | 18 |  | 15 |


| M4 | $\underline{S}$ | M5 | $\underline{\text { S }}$ | M6 | $\underline{\mathbf{S}}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Adam+Ellen | 6 | Adam+Fran | 4 | Adam+Fran | 4 |
| Bob+Fran | 5 | Bob+Diana | 6 | Bob+Ellen | 5 |
| Carl+Diana | 5 | Carl+Ellen | 9 | Carl+Diana | 5 |
| Total | 16 |  | 19 |  | 14 |

## Program 3

## - Program 3: Match-Making

- Must use recursion
- Must use permutations (this SAME algorithm)
- Points to ponder:
- The assignment says that you will try ALL possible matchings
- So think about what it is that you need to permute
- And once you finish any given permutation
- k == \# of people to permute
- What do you do at this point?
- Compute the likeability quotient
- Is it better than previous best quotient?
- Is it a tie? If so, what to do?


## Big-O Notation

$\square$ What is Big O?

- Big O comes from Big-O Notation
- In C.S., we want to know how efficient an algorithm is...how "fast" it is
- More specifically...we want to know how the performance of an algorithm responds to changes in problem size
- The goal is to provide a qualitative insight on the \# of operations for a problem size of $n$ elements.
- And this total \# of operations can be described with a mathematical expression in terms of $n$.
- This expression is known as Big-O


## More Algorithm Analysis

- Examples of Analyzing Code:
- We now go over many examples of code fragments
- Each of these functions will be analyzed for their runtime in terms of the variable $n$
- Utilizing the idea of Big-O,
- determine the Big-O running time of each


## More Algorithm Analysis

- Example 1:
- Determine the Big O running time of the following code fragment:

```
for (k = 1; k <= n/2; k++) {
            sum = sum + 5;
}
for (j = 1; j <= n*n; j++) {
    delta = delta + 1;
}
```


## More Algorithm Analysis

## - Example 1:

- So look at what's going on in the code:
- We care about the total number of REPETITIVE operations.
- Remember, we said we care about the running time for LARGE values of $n$
- So in a for loop with $n$ as part of the comparison value determining when to stop for ( $k=1$; $k<=\underline{n} / 2$; $k++$ )
- Whatever is INSIDE that loop will be executed a LOT of times
- So we examine the code within this loop and see how many operations we find
- When we say operations, we're referring to mathematical operations such as $+,-, *, l$, etc.


## More Algorithm Analysis

## - Example 1:

- So look at what's going on in the code:
- The number of operations executed by these loops is the sum of the individual loop operations.
- We have 2 loops,
- The first loop runs n/2 times
- Each iteration of the first loop results in one operation
- The + operation in: sum = sum + 5;
- So there are $n / 2$ operations in the first loop
- The second loop runs $n^{2}$ times
- Each iteration of the second loop results in one operation
- The + operation in: delta = delta + 1;
- So there are $\mathrm{n}^{2}$ operations in the second loop.


## More Algorithm Analysis

## - Example 1:

- So look at what's going on in the code:
- The number of operations executed by these loops is the sum of the individual loop operations.
- The first loop has $n / 2$ operations
- The second loop has $\mathrm{n}^{2}$ operations
- They are NOT nested loops.
- One loop executes AFTER the other completely finishes
- So we simply ADD their operations
- The total number of operations would be $n / 2+n^{2}$
- In Big-O terms, we can express the number of operations as $\mathrm{O}\left(\mathrm{n}^{2}\right)$


## More Algorithm Analysis

- Example 2:
- Determine the Big O running time of the following code fragment:

```
int func1(int n) {
    int i, j, x = 0;
    for (i = 1; i <= n; i++) {
        for (j = 1; j <= n; j++) {
        }
    }
    return x;
}
```


## More Algorithm Analysis

- Example 2:
- So look at what's going on in the code:
- We care about the total number of REPETITIVE operations
- We have two loops
- AND they are NESTED loops
- The outer loop runs $n$ times
- From i = 1 up through n
- How many operations are performed at each iteration?
- Answer is coming...
- The inner loop runs n times
- From j = 1 up through n
- And only one operation ( $\mathrm{x}++$ ) is performed at each iteration


## More Algorithm Analysis

## - Example 2:

- So look at what's going on in the code:
- Let's look at a couple of iterations of the OUTER loop:
- When i = 1, what happens?
- The inner loop runs $n$ times
- Resulting in $n$ operations from the inner loop
- Then, i gets incremented and it becomes equal to 2
- When $\mathrm{i}=2$, what happens?
- Again, the inner loop runs $n$ times
- Again resulting in $n$ operations from the inner loop
- We notice the following:
- For EACH iteration of the OUTER loop,
- The INNER loop runs $n$ times
- Resulting in n operations


## More Algorithm Analysis

## - Example 2:

- So look at what's going on in the code:
- And how many times does the outer loop run?
- n times
- So the outer loop runs $n$ times
- And for each of those n times, the inner loop also runs n times
- Resulting in n operations
- So we have n operations per iteration of OUTER loop
- And outer loop runs $n$ times
- Finally, we have n*n as the number of operations
- We approximate the running time as $\mathrm{O}\left(\mathrm{n}^{2}\right)$


## More Algorithm Analysis

- Example 3:
- Determine the Big O running time of the following code fragment:

```
int func3(int n) {
    int i, x = 0;
    for (i = 1; i <= n; i++)
        x++;
    for (i = 1; i<=n; i++)
        x++;
    return x;
}
```


## More Algorithm Analysis

- Example 3:
- So look at what's going on in the code:
- We care about the total number of REPETITIVE operations
- We have two loops
- They are NOT nested loops
- The first loop runs $n$ times
- From i = 1 up through n
- only one operation $(x++)$ is performed at each iteration
- How many times does the second loop run?
- Notice that $i$ is indeed reset to 1 at the beginning of the loop
- Thus, the second loop runs $n$ times, from $i=1$ up through $n$
- And only one operation ( $\mathrm{x}++$ ) is performed at each iteration


## More Algorithm Analysis

## - Example 3:

- So look at what's going on in the code:
- Again, the loops are NOT nested
- So they execute sequentially (one after the other)
- Therefore:
- Our total runtime is on the order of $n+n$
- Which of course equals 2 n
- Now, in Big O notation
- We approximate the running time as $\mathrm{O}(\mathrm{n})$


## More Algorithm Analysis

- Example 4:
- Determine the Big O running time of the following code fragment:

```
int func4(int n) {
        while (n > 0) {
        printf("%d", n%2);
        n = n/2;
    }
}
```


## More Algorithm Analysis

- Example 4:
- So look at what's going on in the code:
- We have one while loop
- You can't just look at this loop and say it iterates n times or n/2 times
- Rather, it continues to execute as long as n is greater than 0
- The question is: how many iterations will that be?
- Within the while loop
- The last line of code divides the input, n, by 2
- So $n$ is halved at each iteration of the while loop
- If you remember, we said this ends up running in $\log \mathrm{n}$ time
- Now let's look at how this works


## More Algorithm Analysis

## - Example 4:

- So look at what's going on in the code:
- For the ease of the analysis, we make a new variable
- originalN:
- originalN refers to the value originally stored in the input, $n$
- So if $n$ started at 100 , originalN will be equal to 100
- The first time through the loop
- n gets set to originalN/2
- If the original n was 100, after one iteration n would be 100/2
- The second time through the loop
- n gets set to originalN/4
- The third time through the loop
- n gets set to originalN/8


## More Algorithm Analysis

- Example 4:
- So look at what's going on in the code:
- In general, after kiterations
- n gets set to originalN/2k
- The algorithm ends when original $\mathrm{N} / 2^{\mathrm{k}}=1$, approximately
- We now solve for k
- Why?
- Because we want to find the total \# of iterations
- Multiplying both sides by $2^{k}$, we get originalN $=2^{k}$
- Now, using the definition of logs, we solve for $k$
- $k=\log$ originalN
- So we approximate the running time as $O(\log n)$


## Brief Interlude: Human Stupidity



## More Algorithm Analysis

- Example 5:
- Determine the Big O running time of the following code fragment:

```
int func5(int** array, int n)
    int i = 0, j = 0;
    while (i < n) {
        while (j < n && array[i][j] == 1)
        j++;
        i++;
    }
    return j;
}
```


## More Algorithm Analysis

- Example 5:
- So look at what's going on in the code:
- At first glance, we see two NESTED loops
- This can often indicate an $\mathrm{O}\left(\mathrm{n}^{2}\right)$ algorithm
- But we need to look closer to confirm
- Focus on what's going on with $i$ and $j$

```
int func5(int** array, int n)
    int i = 0, j = 0;
    while (i < n) {
        while (j < n && array[i][j] == 1)
        j++;
    i++;
    }
```


## More Algorithm Analysis

- Example 5:
- So look at what's going on in the code:
- Focus on what's going on with $i$ and $j$
- i and j clearly increase (from the j++ and i++)
- BUT, they never decrease
- AND, neither ever gets reset to 0

```
int func5(int** array, int n)
    int i = 0, j = 0;
    while (i < n) {
        while (j < n && array[i][j] == 1)
        j++;
    i++;
    }
```


## More Algorithm Analysis

- Example 5:
- So look at what's going on in the code:
- And the OUTER while loop ends once i gets to $n$
- So, what does this mean?
- The statement $i++$ can never run more than $n$ times
- And the statement $j++$ can never run more than $n$ times

```
int func5(int** array, int n) {
int i = 0, j = 0;
while (i < n) {
    while (j < n && array[i][j] == 1)
    j++;
    i++;
}
```


## More Algorithm Analysis

- Example 5:
- So look at what's going on in the code:
- The MOST number of times these two statements can run (combined) is 2 n times
- So we approximate the running time as $O(n)$

```
int func5(int** array, int n)
    int i = 0, j = 0;
    while (i < n) {
        while (j < n && array[i][j] == 1)
        j++;
    i++;
    }
```


## More Algorithm Analysis

- Example 6:
- Determine the Big O running time of the following code fragment:
- What's the one big difference here???

```
int func6(int** array, int n) {
    int i = 0, j;
    while (i < n) {
        j = 0;
        while (j < n && array[i][j] == 1)
                        j++;
        i++;
    }
    return j;
}
```


## More Algorithm Analysis

- Example 6:
- So look at what's going on in the code:
- The difference is that we RESET $j$ to 0 a the beginning of the OUTER while loop

```
int func6(int** array, int n) {
    int i = 0, j;
    while (i < n) {
        j = 0;
        while (j < n && array[i][j] == 1)
                        j++;
        i++;
    }
    return j;
}
```


## More Algorithm Analysis

## - Example 6:

- So look at what's going on in the code:
- The difference is that we RESET $j$ to 0 a the beginning of the OUTER while loop
- How does that change things?
- Now j can iterate from 0 to $n$ for EACH iteration of the OUTER while loop
- For each value of $i$
- This is similar to the $2^{\text {nd }}$ example shown
- So we approximate the running time as $O\left(n^{2}\right)$


## More Algorithm Analysis

- Example 7:
- Determine the Big O running time of the following code fragment:

```
int func7(int A[], int sizeA, int B[], int sizeB) {
    int i, j;
    for (i = 0; i < sizeA; i++)
    for (j = 0; j < sizeB; j++)
        if (A[i] == B[j])
                                return 1;
    return 0;
}
```


## More Algorithm Analysis

- Example 7:
- So look at what's going on in the code:
- First notice that the runtime here is NOT in terms of $n$
- It will be in terms of sizeA and sizeB
- And this is also just like Example 2
- The outer loop runs sizeA times
- For EACH of those times,
- The inner loop runs sizeB times
- So this algorithm runs sizeA*sizeB times
- We approximate the running time as O(sizeA*sizeB)


## More Algorithm Analysis

- Example 8:
- Determine the Big O running time of the following code fragment:

```
int func8(int A[], int sizeA, int B[], int sizeB) {
    int i, j;
    for (i = 0; i < sizeA; i++) {
            if (binSearch(B, sizeB, A[i]))
                        return 1;
    }
    return 0;
}
```


## More Algorithm Analysis

## - Example 8:

- So look at what's going on in the code:
- Note: we see that we are calling the function binSearch
- As discussed previously, a single binary search runs in O(log $n$ ) time
- where n represents the number of items within which you are searching
- Examining the for loop:
- The for loop will execute sizeA times
- For EACH iteration of this loop
- a binary search will be run
- We approximate the running time as O(sizeA*log(sizeB))


## More Algorithm Analysis

## WASN'T <br> THAT <br> SWEET!

## Daily Demotivator



Let's Agree to Respect Each Other's Views, No Matter How Wrong Youss May Be.

## More Algorithm Analysis

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