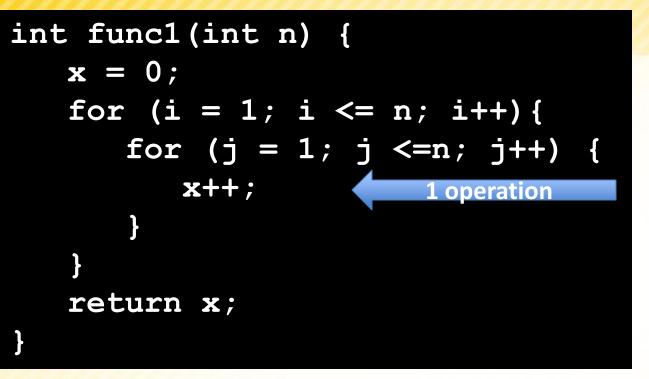


INTRO TO ALGORITHM ANALYSIS

COP 3502

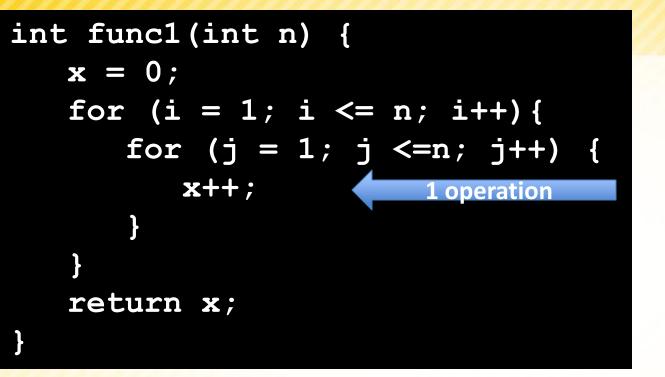
- Each of the following examples illustrates how to determine the Big-O run time of a segment of code or a function.
 - Each of these functions will be analyzed for their runtime in terms of the variable n.
 - Keep in mind that run-time may be dependent on more than one input variable.





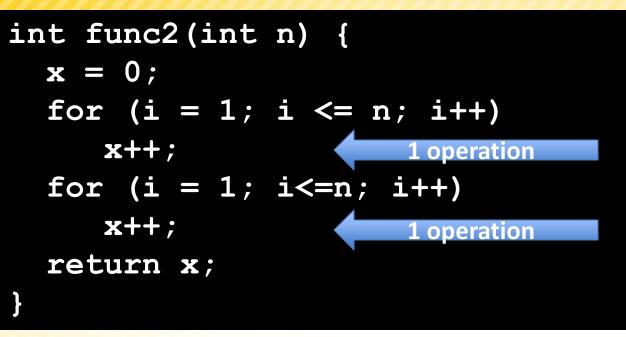
- This is a straight-forward function to analyze
 - We only care about the simple ops in terms of n, remember any constant # of simple steps counts as 1.
 - Let's make a chart for the different values of (i,j), since for each change in i,j we do a constant amount of work.

| i | j |
|------------------------------|------------------------------|
| 1 | 1 |
| 1 | 2 |
| 1 | 3 |
| ••• | |
| 1 | n |
| 2 | 1 |
| 2 | 2 |
| 2 | 3 |
| | |
| 2 | n |
| | |
| n | 1 |
| | |
| n | n |
| 2 2 2 n | 2 3 n 1 |



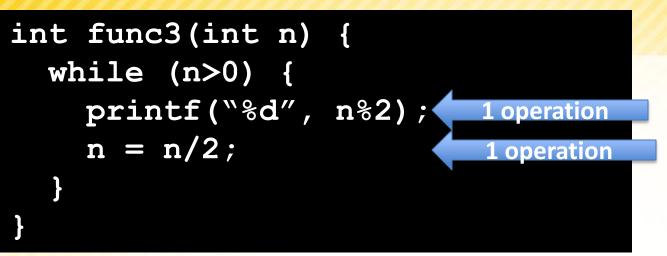
- So for each value of *i*, we do *n* steps.
- n+n+n+...+n
- = n * n
- = O(n²)

| i | j |
|--------|---|
| 1 | 1 |
| 1 | 2 |
| 1 | 3 |
| | |
| 1 | n |
| 2 2 | 1 |
| 2 | 2 |
| 2 | 3 |
| | |
| 2 | n |
| | |
| n | 1 |
| | |
| n | n |

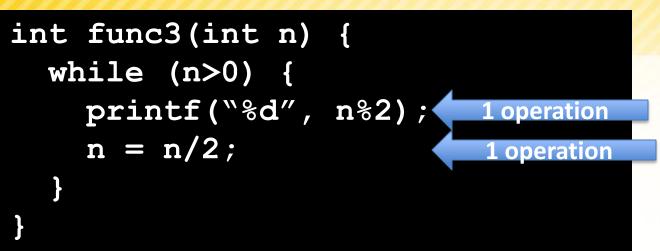


- In this situation, the first for loop runs n times, so we do n steps.
- After it finishes, we run the second for loop which also runs n times.
- Our total runtime is on the order of n+ n = 2 n.
 - In order notation, we drop all leading constants, so our runtime is





- Since n is changing, let origN be the original value of the variable n in the function.
 - The 1st time through the loop, n gets set to origN/2
 - The 2nd time through the loop, n gets set to origN/4
 - The 3rd time through the loop, n gets set to origN/8
 - In general, after k loops, n get set to origN/2^k
- So the algorithm ends when origN/2^k = 1 approximate



- So the algorithm ends when origN/2^k = 1 approximately
 - (where k is the number of steps)
 - \rightarrow origN = 2^k
 - take log of both sides
 - $\rightarrow \log_2(\text{origN}) = \log_2(2^k)$
 - → $\log_2(\text{origN}) = k$
 - So the runtime of this function is

O(lg n)

Note:

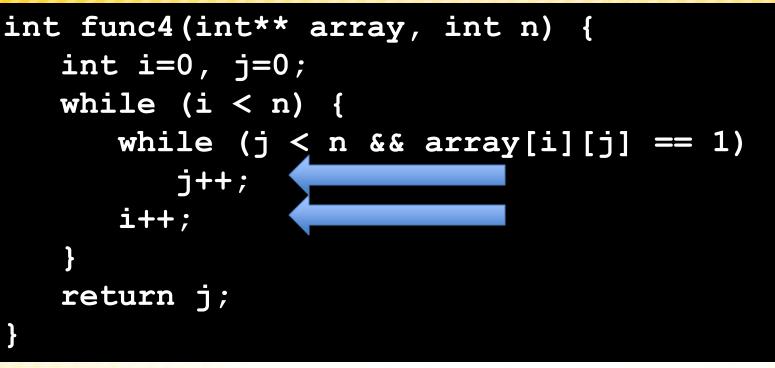
When we use logs in run-time, we omit the base, since for all log functions with different bases greater than 1, they are all equivalent with respect to order notation

Logarithms

Sidenote:

- We never use bases for logarithms in O-notation
- This is because changing bases of logs just involves multiplying by a suitable constant
 - and we don't care about constant of proportionality for Onotation!
- For example:
- If we have log₁₀n and we want it in terms of log₂n
 - \geq We know $\log_{10}n = \log_2 n/\log_2 10$
 - > Where 1/log₂10 = 0.3010
 - \geq Then we get \log_{10} n = 0.3010 x \log_2 n

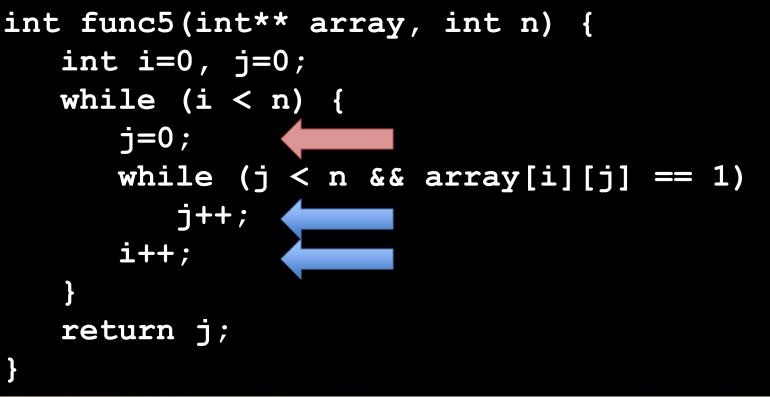




- In this function, i and j can increase, but they can never decrease.
 - Furthermore, the code will stop when *i* gets to *n*.
 - Thus, the statement *i++* can never run more than *n* times and the statement *j++* can never run more than *n* times.
 - Thus, the most number of times these two critical statements can run is 2n.
 - It follows that the runtime of this segment of code is



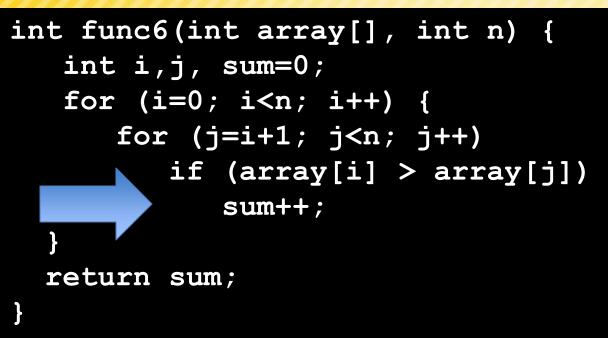
• <u>O(n)</u>



- All we did in this example is reset j to 0 at the beginning of i loop iteration.
 - Now, j can range from 0 to n for EACH value of i
 - (similar to example #1),
 - so the run-time is





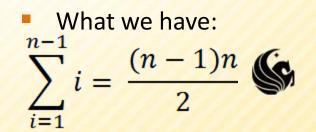


| i | j | value |
|-----|------------|-------|
| 0 | 1,2,3,,n-1 | n-1 |
| 1 | 2,3,4,,n-1 | n-2 |
| 2 | 3,4,5,,n-1 | n-3 |
| | | |
| n-1 | nothing | 0 |

- The amount of times the inner loop runs is dependent on *i*
 - The table shows how j changes w/respect to i
 - The # of times the inner loop runs is the sum:
 - 0 + 1 + 2 + 3 + ... + (n-1)
 - = (n-1)n/2 = 0.5n² 0.5n
 - So the run time is?

<u>O(n²)</u>

Common Summation: $\sum_{i=1}^{n} i = \frac{n(n+1)}{2}$



```
int f7(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;</pre>
```

}

- This runtime is in terms of sizea and sizeb.
- Clearly, similar to Example #1, we simply multiply the # of terms in the 1st loop by the number of terms in the 2nd loop.
- Here, this is simply sizea*sizeb.
- So the runtime is? O(sizea*sizeb)



```
int f7(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;</pre>
```

}

- This runtime is in terms of sizea and sizeb.
- Clearly, similar to Example #1, we simply multiply the # of terms in the 1st loop by the number of terms in the 2nd loop.
- Here, this is simply sizea*sizeb.
- So the runtime is? O(sizea*sizeb)



int f8(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;</pre>
```

- As previously discussed, a single binary search runs in O(lg n)
 - where *n* represents the number of items in the original list you're searching.
- In this particular case, the runtime is? O(sizea*lg(sizeb))
 - since we run our binary search on sizeb items exactly sizea times.



int f8(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;</pre>
```

- In this particular case, the runtime is? O(sizea*lg(sizeb))
 - since we run our binary search on sizeb items exactly sizea times.
- Notice:
 - that the runtime for this algorithm changes greatly if we switch the order of the arrays. Consider the 2 following examples:
 - **1)** *sizea* = 1000000, *sizeb* = 10

sizea = 10, *sizeb* = 1000000 sizea*lg(sizeb) ~ 300

