"bit twiddling: 1. (pejorative) An exercise in tuning (see tune) in which incredible amounts of time and effort go to produce little noticeable improvement, often with the result that the code becomes incomprehensible."

- The Hackers Dictionary, version 4.4.7
Clicker Question 1

- "My program finds all the primes between 2 and 1,000,000,000 in 1.37 seconds."
  - how efficient is my solution, in terms of time?

A. Good
B. Bad
C. It depends
Efficiency

- Computer Scientists don’t just write programs.
- They also *analyze* them.
- How efficient is a program?
  - How much time does it take for the program to complete?
  - How much memory does a program use?
  - How do these change as the amount of data changes?
  - What is the difference between the best case and worst case efficiency if any?
Technique

- Informal approach for this class
  - more formal techniques in theory classes

- Many simplifications
  - view algorithms as Java programs
  - count executable statements in program or method
  - find number of statements as function of the amount of data
  - focus on the *dominant term* in the function
int x; // one statement
x = 12; // one statement
int y = z * x + 3 % 5 * x / i; // 1
x++; // one statement
boolean p = x < y && y % 2 == 0 ||
    z >= y * x; // 1
int[] data = new int[100]; // 100
data[50] = x * x + y * y; // 1
Clicker Question 2

What is output by the following code?

```java
int total = 0;
for (int i = 0; i < 13; i++)
    for (int j = 0; j < 11; j++)
        total += 2;
System.out.println(total);
```

A. 24  
B. 120  
C. 143  
D. 286  
E. 338
What is output when method `sample` is called?

```java
public static void sample(int n, int m) {
    int total = 0;
    for (int i = 0; i < n; i++)
        for (int j = 0; j < m; j++)
            total += 5;
    System.out.println(total);
}
```

A. 5
B. n * m
C. n * m * 5
D. n^m
E. (n * m)^5
Example

```java
public int total(int[] values) {
    int result = 0;
    for (int i = 0; i < values.length; i++)
        result += values[i];
    return result;
}
```

- How many statements are executed by method `total` as a function of `values.length`?
- Let $N = \text{values.length}$
  - $N$ is commonly used as a variable that denotes the amount of data.
Counting Up Statements

- `int result = 0; 1`
- `int i = 0; 1`
- `i < values.length; N + 1`
- `i++ N`
- `result += values[i]; N`
- `return total; 1`
- `T(N) = 3N + 4`
- `T(N) is the number of executable statements in method total as function of values.length`
Another Simplification

- When determining complexity of an algorithm we want to simplify things
  - hide some details to make comparisons easier

- Like assigning your grade for course
  - At the end of CS314 your transcript won’t list all the details of your performance in the course
  - it won’t list scores on all assignments, quizzes, and tests
  - simply a letter grade, B- or A or D+

- So we focus on the dominant term from the function and ignore the coefficient
Big O

- The most common method and notation for discussing the execution time of algorithms is *Big O*, also spoken *Order*
- Big O is the *asymptotic execution time* of the algorithm
- Big O is an upper bounds
- It is a mathematical tool
- Hide a lot of unimportant details by assigning a simple grade (function) to algorithms
Formal Definition of Big $O$

- $T(N)$ is $O(F(N))$ if there are positive constants $c$ and $N_0$ such that $T(N) \leq cF(N)$ when $N \geq N_0$
  - $N$ is the size of the data set the algorithm works on
  - $T(N)$ is a function that characterizes the *actual* running time of the algorithm
  - $F(N)$ is a function that characterizes an upper bounds on $T(N)$. It is a limit on the running time of the algorithm. (The typical Big functions table)
  - $c$ and $N_0$ are constants
What it Means

- $T(N)$ is the actual growth rate of the algorithm
  - can be equated to the number of executable statements in a program or chunk of code
- $F(N)$ is the function that bounds the growth rate
  - may be upper or lower bound
- $T(N)$ may not necessarily equal $F(N)$
  - constants and lesser terms ignored because it is a bounding function
Showing $O(N)$ is Correct

- Recall the formal definition of Big O
  - $T(N)$ is $O(F(N))$ if there are positive constants $c$ and $N_0$ such that $T(N) \leq cF(N)$ when $N > N_0$

- Recall method $\text{total}$, $T(N) = 3N + 4$
  - show method $\text{total}$ is $O(N)$.
  - $F(N)$ is $N$

- We need to choose constants $c$ and $N_0$
- how about $c = 4$, $N_0 = 5$?
vertical axis: time for algorithm to complete. (simplified to number of executable statements)

c * F(N), in this case, c = 4, c * F(N) = 4N

T(N), actual function of time. In this case 3N + 4

F(N), approximate function of time. In this case N

No = 5

horizontal axis: N, number of elements in data set
# Typical Big O Functions – "Grades"

<table>
<thead>
<tr>
<th>Function</th>
<th>Common Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N!$</td>
<td>factorial</td>
</tr>
<tr>
<td>$2^N$</td>
<td>Exponential</td>
</tr>
<tr>
<td>$N^d$, $d &gt; 3$</td>
<td>Polynomial</td>
</tr>
<tr>
<td>$N^3$</td>
<td>Cubic</td>
</tr>
<tr>
<td>$N^2$</td>
<td>Quadratic</td>
</tr>
<tr>
<td>$\sqrt[N]{N}$</td>
<td>N Square root N</td>
</tr>
<tr>
<td>$N \log N$</td>
<td>N log N</td>
</tr>
<tr>
<td>$N$</td>
<td>Linear</td>
</tr>
<tr>
<td>$\sqrt{N}$</td>
<td>Root - n</td>
</tr>
<tr>
<td>log $N$</td>
<td>Logarithmic</td>
</tr>
<tr>
<td>1</td>
<td>Constant</td>
</tr>
</tbody>
</table>
Clicker Question 4

Which of the following is true?

A. Method total is $O(N^{1/2})$
B. Method total is $O(N)$
C. Method total is $O(N^2)$
D. Two of A – C are correct
E. All of three of A – C are correct
Dealing with other methods

- What do I do about method calls?
  
  ```java
double sum = 0.0;
for (int i = 0; i < n; i++)
    sum += Math.sqrt(i);
  
  Long way
  – go to that method or constructor and count statements

  Short way
  – substitute the simplified Big O function for that method.
  – if Math.sqrt is constant time, O(1), simply count
    sum += Math.sqrt(i); as one statement.
Dealing With Other Methods

public int foo(int[] data) {
  int total = 0;
  for (int i = 0; i < data.length; i++)
    total += countDups(data[i], data);
  return total;
}

// method countDups is O(N) where N is the
// length of the array it is passed

What is the Big O of foo?

A. O(1)  B. O(N)  C. O(NlogN)
D. O(N^2)  E. O(N!)
// from the Matrix class
public void scale(int factor) {
    for (int r = 0; r < numRows(); r++)
        for (int c = 0; c < numCols(); c++)
            iCells[r][c] *= factor;
}

Assume numRows() = numCols() = N.
In other words, a square Matrix.
numRows and numCols are O(1)

What is the T(N)? What is the Big O?
A. O(1)  B. O(N)  C. O(NlogN)
D. O(N^2)  E. O(N!)
Just Count Loops, Right?

// assume mat is a 2d array of booleans
// assume mat is square with N rows,
// and N columns

int numThings = 0;
for (int r = row - 1; r <= row + 1; r++)
    for (int c = col - 1; c <= col + 1; c++)
        if (mat[r][c])
            numThings++;

What is the order of the above code?
A. O(1)   B. O(N)   C. O(N^2)   D. O(N^3)   E. O(N^{1/2})
It is Not Just Counting Loops

// Second example from previous slide could be rewritten as follows:
int numThings = 0;
if (mat[r-1][c-1]) numThings++;  
if (mat[r-1][c]) numThings++;  
if (mat[r-1][c+1]) numThings++;  
if (mat[r][c-1]) numThings++;  
if (mat[r][c]) numThings++;  
if (mat[r][c+1]) numThings++;  
if (mat[r+1][c-1]) numThings++;  
if (mat[r+1][c]) numThings++;  
if (mat[r+1][c+1]) numThings++;
Sidetrack, the logarithm

- Thanks to Dr. Math
- $3^2 = 9$
- Likewise $\log_3 9 = 2$
  - "The log to the base 3 of 9 is 2."
- The way to think about log is:
  - "the log to the base x of y is the number you can raise x to to get y."
  - Say to yourself "The log is the exponent." (and say it over and over until you believe it.)
  - In CS we work with base 2 logs, a lot
- $\log_2 32 = ?$  $\log_2 8 = ?$  $\log_2 1024 = ?$  $\log_{10} 1000 = ?$
When Do Logarithms Occur

- Algorithms tend to have a logarithmic term when they use a divide and conquer technique.
- the data set keeps getting divided by 2

```java
public int foo(int n) {
    // pre n > 0
    int total = 0;
    while (n > 0) {
        n = n / 2;
        total++;
    }
    return total;
}
```

- What is the order of the above code?
  A. O(1)  B. O(logN)  C. O(N)
  D. O(Nlog N)  E. O(N²)
Significant Improvement – Algorithm with Smaller Big O function

- Problem: Given an array of ints replace any element equal to 0 with the maximum positive value to the right of that element. (If no positive value to the right, leave unchanged.)

Given:

\[0, 9, 0, 13, 0, 0, 7, 1, -1, 0, 1, 0]\]

Becomes:

\[13, 9, 13, 13, 7, 7, 7, 1, -1, 1, 1, 0]\]
Replace Zeros – Typical Solution

```java
public void replace0s(int[] data) {
    for (int i = 0; i < data.length - 1; i++) {
        if (data[i] == 0) {
            int max = 0;
            for (int j = i + 1; j < data.length; j++) {
                max = Math.max(max, data[j]);
            }
            data[i] = max;
        }
    }
}
```

Assume all values are zeros. (worst case)
Example of a **dependent loops**.
public void replace0s(int[] data) {
    int max =
        Math.max(0, data[data.length - 1]);
    int start = data.length - 2;
    for (int i = start; i >= 0; i--) {
        if (data[i] == 0)
            data[i] = max;
        else
            max = Math.max(max, data[i]);
    }
}

Big O of this approach?
A. O(1)   B. O(N)   C. O(NlogN)
D. O(N^2)   E. O(N!)
A Useful Proportion

- Since $F(N)$ is characterizes the running time of an algorithm the following proportion should hold true:

$$\frac{F(N_0)}{F(N_1)} \sim \frac{\text{time}_0}{\text{time}_1}$$

- An algorithm that is $O(N^2)$ takes 3 seconds to run given 10,000 pieces of data.
  - How long do you expect it to take when there are 30,000 pieces of data?
  - common mistake
  - logarithms?
Why Use Big O?

- As we build data structures Big O is the tool we will use to decide under what conditions one data structure is better than another.
- Think about performance when there is a lot of data.
  - "It worked so well with small data sets..."
  - Joel Spolsky, Schlemiel the painter's Algorithm
- Lots of trade offs
  - some data structures good for certain types of problems, bad for other types
  - often able to trade SPACE for TIME.
  - Faster solution that uses more space
  - Slower solution that uses less space
Big O Space

- Big O could be used to specify how much space is needed for a particular algorithm – in other words how many variables are needed

- Often there is a *time – space tradeoff*
  – can often take less time if willing to use more memory
  – can often use less memory if willing to take longer
  – truly beautiful solutions take less time and space

*The biggest difference between time and space is that you can't reuse time.* - Merrick Furst
Quantifiers on Big O

- It is often useful to discuss different cases for an algorithm
- Best Case: what is the best we can hope for?
  - least interesting
- Average Case (a.k.a. expected running time): what usually happens with the algorithm?
- Worst Case: what is the worst we can expect of the algorithm?
  - very interesting to compare this to the average case
Best, Average, Worst Case

- To Determine the best, average, and worst case Big O we must make assumptions about the data set.

- Best case -> what are the properties of the data set that will lead to the fewest number of executable statements (steps in the algorithm).

- Worst case -> what are the properties of the data set that will lead to the largest number of executable statements.

- Average case -> Usually this means assuming the data is randomly distributed.
  - or if I ran the algorithm a large number of times with different sets of data what would the average amount of work be for those runs?
Another Example

```java
public double minimum(double[] values) {
    int n = values.length;
    double minValue = values[0];
    for (int i = 1; i < n; i++)
        if (values[i] < minValue)
            minValue = values[i];
    return minValue;
}
```

- $T(N)$? $F(N)$? $\text{Big O}$? $\text{Best case}$? $\text{Worst Case}$? $\text{Average Case}$?
- If no other information, assume asking average case
Example of Dominance

- Look at an extreme example. Assume the actual number as a function of the amount of data is:

\[ \frac{N^2}{10000} + 2N \log_{10} N + 100000 \]

- Is it plausible to say the \( N^2 \) term dominates even though it is divided by 10000 and that the algorithm is \( O(N^2) \)?

- What if we separate the equation into \( \frac{N^2}{10000} \) and \( 2N \log_{10} N + 100000 \) and graph the results.
For large values of $N$ the $N^2$ term dominates so the algorithm is $O(N^2)$

When does it make sense to use a computer?
Comparing Grades

- Assume we have a problem
- Algorithm A solves the problem correctly and is $O(N^2)$
- Algorithm B solves the same problem correctly and is $O(N \log_2 N)$
- Which algorithm is faster?
- One of the assumptions of Big O is that the data set is large.
- The "grades" should be accurate tools if this is true.
Running Times

- Assume $N = 100,000$ and processor speed is $1,000,000,000$ operations per second

<table>
<thead>
<tr>
<th>Function</th>
<th>Running Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$2^N$</td>
<td>$3.2 \times 10^{30,086}$ years</td>
</tr>
<tr>
<td>$N^4$</td>
<td>3171 years</td>
</tr>
<tr>
<td>$N^3$</td>
<td>11.6 days</td>
</tr>
<tr>
<td>$N^2$</td>
<td>10 seconds</td>
</tr>
<tr>
<td>$\sqrt{N}$</td>
<td>0.032 seconds</td>
</tr>
<tr>
<td>$N \log N$</td>
<td>0.0017 seconds</td>
</tr>
<tr>
<td>$N$</td>
<td>0.0001 seconds</td>
</tr>
<tr>
<td>$\sqrt{N}$</td>
<td>$3.2 \times 10^{-7}$ seconds</td>
</tr>
<tr>
<td>$\log N$</td>
<td>$1.2 \times 10^{-8}$ seconds</td>
</tr>
</tbody>
</table>
Theory to Practice OR
Dykstra says: "Pictures are for the Weak."

<table>
<thead>
<tr>
<th></th>
<th>1000</th>
<th>2000</th>
<th>4000</th>
<th>8000</th>
<th>16000</th>
<th>32000</th>
<th>64000</th>
<th>128K</th>
</tr>
</thead>
<tbody>
<tr>
<td>O(N)</td>
<td>2.2x10^{-5}</td>
<td>2.7x10^{-5}</td>
<td>5.4x10^{-5}</td>
<td>4.2x10^{-5}</td>
<td>6.8x10^{-5}</td>
<td>1.2x10^{-4}</td>
<td>2.3x10^{-4}</td>
<td>5.1x10^{-4}</td>
</tr>
<tr>
<td>O(NlogN)</td>
<td>8.5x10^{-5}</td>
<td>1.9x10^{-4}</td>
<td>3.7x10^{-4}</td>
<td>4.7x10^{-4}</td>
<td>1.0x10^{-3}</td>
<td>2.1x10^{-3}</td>
<td>4.6x10^{-3}</td>
<td>1.2x10^{-2}</td>
</tr>
<tr>
<td>O(N^{3/2})</td>
<td>3.5x10^{-5}</td>
<td>6.9x10^{-4}</td>
<td>1.7x10^{-3}</td>
<td>5.0x10^{-3}</td>
<td>1.4x10^{-2}</td>
<td>3.8x10^{-2}</td>
<td>0.11</td>
<td>0.30</td>
</tr>
<tr>
<td>O(N^2) ind.</td>
<td>3.4x10^{-3}</td>
<td>1.4x10^{-3}</td>
<td>4.4x10^{-3}</td>
<td>0.22</td>
<td>0.86</td>
<td>3.45</td>
<td>13.79</td>
<td>(55)</td>
</tr>
<tr>
<td>O(N^2) dep.</td>
<td>1.8x10^{-3}</td>
<td>7.1x10^{-3}</td>
<td>2.7x10^{-2}</td>
<td>0.11</td>
<td>0.43</td>
<td>1.73</td>
<td>6.90</td>
<td>(27.6)</td>
</tr>
<tr>
<td>O(N^3)</td>
<td>3.40</td>
<td>27.26</td>
<td>(218)</td>
<td>(1745)</td>
<td>(13,957)</td>
<td>(112k)</td>
<td>(896k)</td>
<td>(7.2m)</td>
</tr>
</tbody>
</table>

*Times in Seconds.* Red indicates predicated value.
## Change between Data Points

<table>
<thead>
<tr>
<th>Complexity</th>
<th>1000</th>
<th>2000</th>
<th>4000</th>
<th>8000</th>
<th>16000</th>
<th>32000</th>
<th>64000</th>
<th>128K</th>
<th>256k</th>
<th>512k</th>
</tr>
</thead>
<tbody>
<tr>
<td>O(N)</td>
<td>-</td>
<td>1.21</td>
<td>2.02</td>
<td>0.78</td>
<td>1.62</td>
<td>1.76</td>
<td>1.89</td>
<td>2.24</td>
<td>2.11</td>
<td>1.62</td>
</tr>
<tr>
<td>O(N\log N)</td>
<td>-</td>
<td>2.18</td>
<td>1.99</td>
<td>1.27</td>
<td>2.13</td>
<td>2.15</td>
<td>2.15</td>
<td>2.71</td>
<td>1.64</td>
<td>2.40</td>
</tr>
<tr>
<td>O(N^{3/2})</td>
<td>-</td>
<td>1.98</td>
<td>2.48</td>
<td>2.87</td>
<td>2.79</td>
<td>2.76</td>
<td>2.85</td>
<td>2.79</td>
<td>2.82</td>
<td>2.81</td>
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<tr>
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<td>-</td>
<td>4.06</td>
<td>3.98</td>
<td>3.94</td>
<td>3.99</td>
<td>4.00</td>
<td>3.99</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td>O(N^2) dep</td>
<td>-</td>
<td>4.00</td>
<td>3.82</td>
<td>3.97</td>
<td>4.00</td>
<td>4.01</td>
<td>3.98</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>O(N^3)</td>
<td>-</td>
<td>8.03</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

### Value obtained by \( \frac{\text{Time}_x}{\text{Time}_{x-1}} \)
Okay, Pictures

Results on a 2GhZ laptop

<table>
<thead>
<tr>
<th>Value of N</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>NlogN</td>
<td>NlogN</td>
</tr>
<tr>
<td>NsqrtN</td>
<td>NsqrtN</td>
</tr>
<tr>
<td>N^2</td>
<td>N^2</td>
</tr>
</tbody>
</table>

Value of N: 0.0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0
Time: 0.0, 5000, 10000, 15000, 20000, 25000, 30000, 35000

CS 314 Efficiency - Complexity
Put a Cap on Time

Results on a 2Ghz laptop

<table>
<thead>
<tr>
<th>Value of N</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td></td>
</tr>
<tr>
<td>NlogN</td>
<td></td>
</tr>
<tr>
<td>NsqrtN</td>
<td></td>
</tr>
<tr>
<td>N^2</td>
<td></td>
</tr>
</tbody>
</table>
No $O(N^2)$ Data

Results on a 2GhZ laptop

![Graph showing results on a 2GhZ laptop with lines for $N$, $N\log N$, and $N^{1/2}$]
Just $O(N)$ and $O(N\log N)$

![Graph showing time (Y-axis) vs. value of N (X-axis) for $N$ and $N\log N$.

- The $N$ line is a straight line indicating linear growth.
- The $N\log N$ line is a curve indicating slower growth.

Results on a 2Ghz laptop

- Values tested range from 0 to 600,000.
- The graph shows the time taken for operations with different values of N.
Just $O(N)$
10^9 instructions/sec, runtimes

<table>
<thead>
<tr>
<th>N</th>
<th>O(log N)</th>
<th>O(N)</th>
<th>O(N log N)</th>
<th>O(N^2)</th>
</tr>
</thead>
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<td>0.00000001</td>
<td>0.000000033</td>
<td>0.0000001</td>
</tr>
<tr>
<td>100</td>
<td>0.000000007</td>
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<td>0.000000664</td>
<td>0.0001000</td>
</tr>
<tr>
<td>1,000</td>
<td>0.000000010</td>
<td>0.00000100</td>
<td>0.00010000</td>
<td>0.001</td>
</tr>
<tr>
<td>10,000</td>
<td>0.000000013</td>
<td>0.00010000</td>
<td>0.00132900</td>
<td>0.1 min</td>
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<tr>
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<td>0.000000017</td>
<td>0.0010000</td>
<td>0.01661000</td>
<td>10 seconds</td>
</tr>
<tr>
<td>1,000,000</td>
<td>0.000000020</td>
<td>0.001</td>
<td>0.0199</td>
<td>16.7 minutes</td>
</tr>
<tr>
<td>1,000,000,000</td>
<td>0.000000030</td>
<td>1.0 second</td>
<td>30 seconds</td>
<td>31.7 years</td>
</tr>
</tbody>
</table>
Formal Definition of Big O (repeated)

- \( T(N) \) is \( \text{O}( F(N) ) \) if there are positive constants \( c \) and \( N_0 \) such that \( T(N) \leq cF(N) \) when \( N \geq N_0 \)
  - \( N \) is the size of the data set the algorithm works on
  - \( T(N) \) is a function that characterizes the \textit{actual} running time of the algorithm
  - \( F(N) \) is a function that characterizes an upper bounds on \( T(N) \). It is a limit on the running time of the algorithm
  - \( c \) and \( N_0 \) are constants
More on the Formal Definition

- There is a point $N_0$ such that for all values of $N$ that are past this point, $T(N)$ is bounded by some multiple of $F(N)$

- Thus if $T(N)$ of the algorithm is $O(N^2)$ then, ignoring constants, at some point we can *bound* the running time by a quadratic function.

- Given a *linear* algorithm it is *technically correct* to say the running time is $O(N^2)$. $O(N)$ is a more precise answer as to the Big O of the linear algorithm
  - thus the caveat “pick the most restrictive function” in Big O type questions.
What it All Means

- $T(N)$ is the actual growth rate of the algorithm
  - can be equated to the number of executable statements in a program or chunk of code

- $F(N)$ is the function that bounds the growth rate
  - may be upper or lower bound

- $T(N)$ may not necessarily equal $F(N)$
  - constants and lesser terms ignored because it is a bounding function
Other Algorithmic Analysis Tools

- **Big Omega** $T(N)$ is $\Omega(F(N))$ if there are positive constants $c$ and $N_0$ such that $T(N) \geq cF(N)$ when $N \geq N_0$
  - Big O is similar to less than or equal, an upper bound
  - Big Omega is similar to greater than or equal, a lower bound

- **Big Theta** $T(N)$ is $\Theta(F(N))$ if and only if $T(N)$ is $O(F(N))$ and $T(N)$ is $\Omega(F(N))$.
  - Big Theta is similar to equals
### Relative Rates of Growth

<table>
<thead>
<tr>
<th>Analysis Type</th>
<th>Mathematical Expression</th>
<th>Relative Rates of Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big $O$</td>
<td>$T(N) = O( F(N) )$</td>
<td>$T(N) \leq F(N)$</td>
</tr>
<tr>
<td>Big $\Omega$</td>
<td>$T(N) = \Omega( F(N) )$</td>
<td>$T(N) \geq F(N)$</td>
</tr>
<tr>
<td>Big $\theta$</td>
<td>$T(N) = \theta( F(N) )$</td>
<td>$T(N) = F(N)$</td>
</tr>
</tbody>
</table>

"In spite of the additional precision offered by Big Theta, Big $O$ is more commonly used, except by researchers in the algorithms analysis field" - Mark Weiss