## Big-Oh Notation

Informally, we say that an algorithm that operations on input of size n is worst-case $\mathrm{O}(\mathrm{f}(\mathrm{n})$ ) (e.g. $O\left(n^{2}\right)$ ) if for large values of $n$ the algorithm uses no more than a fixed constant times $f(n)$ basic operations. For example, we will show that the BubbleSort algorithm uses no more than $2 \mathrm{n}(\mathrm{n}-1)$ operations; this is certainly no more than $2 n^{2}$, which is a multiple of $n^{2}$, so BubbleSort is worst-case $\mathrm{O}\left(\mathrm{n}^{2}\right)$.

Stylistically, we try to keep the orders as simple as possible. Since there is an arbitrary constant factor $O\left(n^{2}\right)$ is the same as $O\left(23 n^{2}\right)$, which in turn is the same as $O\left(23 n^{2}+5 n+6\right)$. We represent all of these as $\mathrm{O}\left(\mathrm{n}^{2}\right)$.

There are several symbols like O:

- $\mathrm{O}(\mathrm{f}(\mathrm{n})$ ) (Big-Oh) represents an upper bound -- for large n the algorithm is no worse than a constant times $f(n)$, but it might be better.
- $\Omega(f(n))$ (Big-Omega) represents a lower bound -- for large $n$ the algorithm is no better than a constant times $f(n)$.
- $\Theta(f(n))$ (Big-Theta) represents both an upper and a lower bound. - o( $f(n))$ (Little-Oh) is a strict upper bound: $O(f(n))$ and not $\Omega(f(n))$

This semester we will use Big-Oh almost exclusively.

Here are a few formal definitions for the mathematically inclined:

- We say function $T(n)$ is $O(f(n))$ if there are constants $k$ and $N$ so that for every $n>=N$ we have $T(n)<=k^{*} f(n)$.
- We say $T(n)$ is $\Omega(f(n))$ if there are constants $k$ and $N$ so that for every $n>=N$ we have $T(n)>=$ $k^{*} f(n)$.

Don't worry about these for now.

Here is an addition rule: if $T_{1}(n)$ is $O(f(n))$ and $T_{2}(n)$ is $O(f(n))$ then $T_{1}(n)+T_{2}(n)$ is $O(f(n))$.

For example, $3 n^{3}-2 n^{2}+27$ is $O\left(n^{3}\right)$ because each of its terms is $\mathrm{O}\left(\mathrm{n}^{3}\right)$.

In general, a polynomial of degree k is $\mathrm{O}\left(\mathrm{n}^{\mathrm{k}}\right)$ because each of its terms is $\mathrm{O}\left(\mathrm{n}^{\mathrm{k}}\right)$.

Note that all logarithms are proportional -- if a and $b$ are any two bases, then

$$
\log _{a}(x)=\log _{b}(x)^{*} \log _{a}(b)
$$

If we are only talking about orders of growth, it doesn't matter if we interpret "log" as meaning base-2 logs or base-10 logs or natural logs; each is a constant times each of the others.

