# COMPLEXITY CLASSES EXAMPLES 

(download slides and .py files to follow along)

### 6.100L Lecture 23

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## THETA

- Theta $\Theta$ is how we denote the asymptotic complexity
- We look at the input term that dominates the function
- Drop other pieces that don't have the fastest growth
- Drop additive constants
- Drop multiplicative constants
- End up with only a few classes of algorithms
- We will look at code that lands in each of these classes today


## WHERE DOES THE FUNCTION COME FROM?

- Given code, start with the input parameters. What are they?
- Come up with the equation relating input to number of ops.
- $\mathrm{f}=1+\operatorname{len}(\mathrm{L} 1) * 5+\square+\operatorname{len}(\mathrm{L} 2) * 5+2=5 * \operatorname{len}(\mathrm{~L} 1)+5 * \operatorname{len}(\mathrm{~L} 2)+3$
- If lengths are the same, $f=10 * \operatorname{len}(\mathrm{~L})+3$
- $\Theta(f)=\Theta(10 * \operatorname{len}(\mathrm{~L})+3)=\Theta(\operatorname{len}(\mathrm{L}))$



## WHERE DOES THE FUNCTION COME FROM?

- A quicker way: no need to come up with the exact formula. Look for loops and anything that repeats wrt the input parameters. Everything else is constant.


```
    for i in range(len(L1)):
        if L[i] == L1[i]:
            inL1 = True
inL2 = False
for i in range(len(L2)):
            if L[i] == L2[i]:
                        inL2 = True
return inL1 and inL2
```


## COMPLEXITY CLASSES n is the input

We want to design algorithms that are as close to top of this hierarchy as possible


Elements

- $\Theta$ (1) denotes constant running time
- $\Theta(\log n)$ denotes logarithmic running time
- $\Theta(n)$ denotes linear running time
- $\Theta(n \log n)$ denotes log-linear running time
- $\Theta\left(n^{c}\right)$ denotes polynomial running time (c is a constant)
- $\Theta\left(c^{n}\right)$ denotes exponential running time ( $c$ is a constant raised to a power based on input size)


## CONSTANT COMPLEXITY

## CONSTANT COMPLEXITY

- Complexity independent of inputs
- Very few interesting algorithms in this class, but can often have pieces that fit this class
- Can have loops or recursive calls, but number of iterations or calls independent of size of input
- Some built-in operations to a language are constant
- Python indexing into a list L [ i ]
- Python list append L. append ()
- Python dictionary lookup d [key]


## CONSTANT COMPLEXITY: EXAMPLE 1

```
def add(x, y):
    return x+y
```

- Complexity in terms of either $x$ or $y: ~(1)$


## CONSTANT COMPLEXITY: EXAMPLE 2

$$
\text { def } \begin{aligned}
& \text { convert_to_km }(m): \\
& \text { return } m * 1.609
\end{aligned}
$$

- Complexity in terms of m: $\mathbf{O ( 1 )}$


## CONSTANT COMPLEXITY: EXAMPLE 3

$$
\begin{aligned}
& \text { def } \operatorname{loop}(x): \\
& y=100 \\
& \text { } \begin{array}{l}
\text { total }=0 \\
\\
\text { for i in range }(y): \\
\quad \text { total }+=x \\
\text { return total }
\end{array} .
\end{aligned}
$$

- Complexity in terms of $x$ (the input parameter): $\boldsymbol{\Theta}(1)$


## LINEAR COMPLEXITY

## LINEAR COMPLEXITY

- Simple iterative loop algorithms
- Loops must be a function of input
- Linear search a list to see if an element is present
- Recursive functions with one recursive call and constant overhead for call
- Some built-in operations are linear
- e in L
- Subset of list: e.g. L [: len (L) / / 2]
- L1 == L2
- del (L[5])


## COMPLEXITY EXAMPLE 0 (with a twist)

- Multiply $x$ by $y$
def mul(x, y):

$$
\begin{aligned}
& \text { tot }=0 \\
& \text { for } i \text { in range }(y): \\
& \text { tot }+=x
\end{aligned}
$$

return tot

- Complexity in terms of $y: \Theta(y)$
- Complexity in terms of $x: \Theta(1)$



## BIG IDEA

## Be careful about what the inputs are.

## LINEAR COMPLEXITY: EXAMPLE 1

- Add characters of a string, assumed to be composed of decimal digits

```
def add_digits(s):
    val = 0
    for c in s:
    val += int(c)
    return val
```

- O(len(s))
- $0(n)$ where $n$ is len(s)


## LINEAR COMPLEXITY: EXAMPLE 2

- Loop to find the factorial of a number >=2

```
def fact_iter(n):
    prod = 1
    for i in range(2, n+1):
    prod *= i
```

    return prod
    - Number of times around loop is n-1
- Number of operations inside loop is a constant
- Independent of $n$
- Overall just $\boldsymbol{O}(\mathrm{n})$


## FUNNY THING ABOUT FACTORIAL AND PYTHON

```
iter fact(40) took 3.10e-06 sec (322,580.65/sec)
iter fact(80) took 6.00e-06 sec (166,666.67/sec)
iter fact(160) took[1.34e-05] sec (74,626.87/sec)
iter fact(320) took 3.39e-05 sec (29,498.53/sec)
iter fact(640) took 1.18e-04 sec (8,488.96/sec)
iter fact(1280) took [4.31e-04] sec (2,322.88/sec)
iter fact(2560) took 1.33e-03 sec (752.73/sec)
iter fact(5120) took 4.94e-03 sec (202.24/sec)
iter fact(10240) took 1.90e-02 sec (52.50/sec)
iter fact(20480) took 7.66e-02 sec (13.06/sec)
iter fact(40960) took 3.35e-01 sec (2.99/sec)
iter fact(81920) took 1.60e+00 sec (0.62/sec)
```

- Eventually grows faster than linear
- Because Python increases the size of integers, which yields more costly operations
- For this class: ignore such effects


## LINEAR COMPLEXITY: EXAMPLE 3

```
def fact_recur(n):
    """ assume n >= 0 """
    if }\textrm{n}<=1
        return 1
    else:
        return n*fact_recur(n - 1)
```

- Computes factorial recursively

- If you time it, notice that it runs a bit slower than iterative version due to function calls
- $\Theta(n)$ because the number of function calls is linear in $n$
- Iterative and recursive factorial implementations are the same order of growth


## LINEAR COMPLEXITY: EXAMPLE 4

```
def compound(invest, interest, n_months):
    total=0
                                O(n_months)
    for i in range(n months):
        total = total * interest + invest }\mp@subsup{}{}{*}(1
```

    return total
    - $\Theta(1)^{*} \Theta$ (n_months) $=\Theta$ (n_months) $\Theta(n)$ where $n=n \_m o n t h s$
- If I was being thorough, then need to account for assignment and return statements:
- $\Theta(1)+4^{*} \Theta(n)+\Theta(1)=\Theta\left(1+4^{*} n+1\right)=\Theta(n)$ where $n=n \_m o n t h s$


## COMPLEXITY OF ITERATIVE FIBONACCI

def fib_iter $(\mathrm{n}):$

| if $\mathrm{n}==0:$ |
| ---: |
| return 0 |
| elif $n==1:$ |
| return 1 |


$\Theta(1)+\Theta(1)+\Theta(n) * \Theta(1)+\Theta(1)$
$\rightarrow \Theta(n)$

## POLYNOMIAL COMPLEXITY

## POLYNOMIAL COMPLEXITY (OFTEN QUADRATIC)

- Most common polynomial algorithms are quadratic, i.e., complexity grows with square of size of input
- Commonly occurs when we have nested loops or recursive function calls


## QUADRATIC COMPLEXITY: EXAMPLE 1

```
def g(n):
```


return $x$
times: $\mathbf{O}(\mathbf{n})$ )

- Computes $\mathrm{n}^{2}$ very inefficiently
- Look at the loops. Are they in terms of the input?
- Nested loops
- Look at the ranges
- Each iterating $n$ times
- $\Theta(n) * \Theta(n) * \Theta(1)=\Theta\left(n^{2}\right)$


## QUADRATIC COMPLEXITY: EXAMPLE 2

- Decide if L1 is a subset of L2: are all elements of L1 in L2?

Yes:

```
L1 = [3, 5, 2]
L2 = [2, 3, 5, 9]
```

def is_subset (L1, L2):
for el in L1:
matched $=$ False
for e2 in L2:
if e1 == e2:
matched $=$ True
break
if not matched:
return False
return True

## QUADRATIC COMPLEXITY: EXAMPLE 2

```
def is_subset(L1, L2):
```

    for e1 in L1:
    matched \(=\) False
    for e2 in L2:
        if \(e 1==e 2:\)
        matched \(=\) True
    break
    if not matched:
    return False
    return True

Outer loop executed len(L1) times

Each iteration will execute inner loop up to len(L2) times

O(len(L1)*len(L2))
If L1 and L2 same length and none of elements of L1 in L2
$\Theta\left(\operatorname{len}(\mathrm{L} 1)^{2}\right)$

## QUADRATIC COMPLEXITY: EXAMPLE 3

- Find intersection of two lists, return a list with each element appearing only once
Example:

```
L1 = [3, 5, 2]
L2 = [2, 3, 5, 9]
\[
\text { returns }[2,3,5]
\]
returns [2,3,5]
```

$$
\begin{aligned}
& \mathrm{L} 1=[7,7,7] \\
& \mathrm{L} 2=[7,7,7] \\
& \text { returns }[7]
\end{aligned}
$$

```
def intersect(L1, L2):
```


## QUADRATIC COMPLEXITY: EXAMPLE 3

```
def intersect(L1, L2):
    tmp = []
    for e1 in L1:
        for e2 in L2:
        if e1 == e2:
        tmp.append(e1)
    unique = []
    for e in tmp:
    if not(e in unique):
        unique.append(e)
    return unique
```

First nested loop takes $\Theta$ (len(L1)*len(L2)) steps.

Second loop takes at most O(len(L1)*len(L2)) steps. Typically not this bad.

- E.g: $[7,7,7]$ and $[7,7,7]$ makes tmp $=[7,7,7,7,7,7,7,7,7]$

Overall O(len(L1)*len(L2))

```
DIAMETER COMPLEXITY
def diameter(L):
    farthest dist = 0
    for i in range(len(L))]:
        p1 = L[i]
        p2 = L[j]
        dist = math.sqrt( (p1[0]-p2[0])**2 + (p1[1]-p2[1])**2 )
        if dist > farthest_dist:
            farthest_dist = dist
    return farthest_dist
```

$\operatorname{len}(\mathrm{L}) * \operatorname{len}(\mathrm{~L}) / 2$ iterations $=\operatorname{len}(\mathrm{L})^{2} / 2$
$O\left(\operatorname{len}(\mathrm{~L})^{2}\right)$

## YOU TRY IT!

```
def all digits(nums):
""" nums is a list of numbers """
digits = [0,1,2,3,4,5,6,7,8,9]
for i in nums:
    isin = False
    for j in digits:
        if i == j:
            isin = True
            break
    if not isin:
        return False
return True
```


## ANSWER:

What's the input?
Outer for loop is $\Theta$ (nums).
Inner for loop is $\Theta(1)$.
Overall: $\Theta(\operatorname{len}($ nums))

## YOU TRY IT!

- Asymptotic complexity of f? And if L1,L2,L3 are same length?
def f(L1, L2, L3):
for el in L1:
for e2 in L2:
if e1 in L 3 and e 2 in L 3 :
return True
return False


## ANSWER:

$\Theta(\operatorname{len}(L 1))^{*} \Theta(\operatorname{len}(L 2))^{*} \Theta(\operatorname{len}(L 3)+\operatorname{len}(L 3))$
Overall: $\Theta\left(\operatorname{len}(\mathrm{L} 1)^{*} \operatorname{len}(\mathrm{L2})^{*} \operatorname{len}(\mathrm{~L} 3)\right)$
Overall if lists equal length: $\Theta(\operatorname{len}(L 1) * * 3)$

## EXPONENTIAL COMPLEXITY

## EXPONENTIAL COMPLEXITY

- Recursive functions where have more than one recursive call for each size of problem
- Fibonacci
- Many important problems are inherently exponential
- Unfortunate, as cost can be high
- Will lead us to consider approximate solutions more quickly

$2^{30} \sim=1$ million
$2^{100}>$ \# cycles than all the computers in the world working for all of recorded history ${ }_{32}$ could complete


## COMPLEXITY OF RECURSIVE FIBONACCI

```
def fib_recur(n):
    """-assumes n an int >= 0 """
    if n == 0:
    return 0
    elif n == 1:
    return 1
    else:
        return fib_recur(n-1) + fib_recur(n-2)
```

- Worst case: $0\left(2^{\text {n }}\right)$



## COMPLEXITY OF RECURSIVE FIBONACCI



- Can do a bit better than $2^{n}$ since tree thins out to the right
- But complexity is still order exponential


## EXPONENTIAL COMPLEXITY: GENERATE SUBSETS

- Input is [1, 2, 3]
- Output is all combinations of elements of all lengths $[[],[1],[2],[3],[1,2],[1,3],[2,3],[1,2,3]]$
def gen_subsets(L):

$$
\text { if len }(\mathrm{L})=0 \text { : }
$$


extra $=\mathrm{L}[-1:]$
$\square$
for small in smaller:
new. append (small+extra)
return smaller+new

## VISUALIZING the ALGORITHM



```
def gen_subsets(L):
if len(L) == 0:
    return [[]]
extra = L[-1:]
smaller = gen_subsets(L[:-1])
    new = []
    for small in smaller:
        new.append(small+extra)
    return smaller+new
```


## VISUALIZING the ALGORITHM

def gen_subsets(L):
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if len(L) == 0:
if len(L) == 0:
return [[]]
return [[]]
extra = L[-1:]
extra = L[-1:]
smaller = gen_subsets(L[:-1])
smaller = gen_subsets(L[:-1])
new = []
new = []
for small in smaller:
for small in smaller:
new. append(small+extra)
new. append(small+extra)
return smaller+new
return smaller+new

## VISUALIZING the ALGORITHM



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```
def gen_subsets(L):
    if len(L) == 0:
    return [[]]
    extra = L[-1:]
    smaller = gen_subsets(L[:-1])
new = [] 
    new.append(small+extra)
    return smaller+new
```


## VISUALIZING the ALGORITHM



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    smaller = gen_subsets(L[:-1])
    new = []
    for small in smaller:
    new.append(small+extra)
    return smaller+new
```


## VISUALIZING the ALGORITHM

([],[1],[2],[1,2],[3],[1,3],[2,3],[1,2,3]]

```
def gen_subsets(L):
    if len(L) == 0:
    return [[]]
    extra = L[-1:]
    smaller = gen_subsets(L[:-1])
    new = []
    for small in smaller:
    new.append(small+extra)
    return smaller+new
```


## EXPONENTIAL COMPLEXITY GENERATE SUBSETS

```
def gen_subsets(L):
```

def gen_subsets(L):
if len(L) == 0:
if len(L) == 0:
return [[]]
return [[]]
extra = L[-1:]
extra = L[-1:]
smaller = gen_subsets(L[:-1])
smaller = gen_subsets(L[:-1])
new = []
new = []
for small in smaller:
for small in smaller:
new.append(small+extra)
new.append(small+extra)
return smaller+new

```
    return smaller+new
```

- Assuming append is constant time
- Time to make sublists includes time to solve smaller problem, and time needed to make a copy of all elements in smaller problem


## EXPONENTIAL COMPLEXITY GENERATE SUBSETS

```
def gen_subsets(L):
    if len(L) == 0:
        return [[]]
    extra = L[-1:]
    smaller = gen_subsets(L[:-1])
    new = []
    for small in smaller:
    new.append(small+extra)
    return smaller+new
```

- Think about size of smaller
- For a set of size $k$ there are $2^{k}$ cases, doubling the size every call
- So to solve need $2^{n-1}+2^{n-2}+\ldots$ $+2^{0}$ steps $=\Theta\left(2^{n}\right)$
- Time to make a copy of smaller
- Concatenation isn't constant
- $\Theta(n)$
- Overall complexity is $\theta\left(n^{*} 2^{n}\right)$ where $n=l e n(L)$


## LOGARITHMIC COMPLEXITY

## TRICKY COMPLEXITY



- Adds digits of a number together
- $n=83$, but the loop only iterates 2 times. Relationship?
- $n=4271$, but the loop only iterates 4 times! Relationship?



## TRICKY COMPLEXITY

def digit_add(n):
""" assume $n$ an int $>=0$ """
answer $=0$
$\mathrm{S}=\operatorname{str}(\mathrm{n})$
for C in $\mathrm{s}[::-1]:$
return answer


- Adds digits of a number together
- $n=83$, but the loop only iterates 2 times. Relationship?
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## TRICKY COMPLEXITY

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## TRICKY COMPLEXITY

def digit_add(n):
""" assume $n$ an int $>=0$ """
answer $=0$
$\mathrm{S}=\operatorname{str}(\mathrm{n})$
for C in $\mathrm{s}[::-1]:$
return answer


- Adds digits of a number together
- $n=83$, but the loop only iterates 2 times. Relationship?
- $n=4271$, but the loop only iterates 4 times! Relationship?



## TRICKY COMPLEXITY

```
def digit_add(n):
    """ assume n an int >= 0 """
    answer = 0
    s=str(n)
    for c in s[::-1]:
        answer += int(c)
    return answer
```



- Adds digits of a number together
- Tricky part: iterate over length of string, not magnitude of $n$
- Think of it like dividing $n$ by 10 each iteration
- $\mathrm{n} / 10^{\operatorname{len}(s)}=1$ (i.e. divide by 10 until there is 1 element left to add)
- $\operatorname{len}(\mathrm{s})=\log (\mathrm{n})$
- $\Theta(\log n)$ - base doesn't matter


## LOGARITHMIC COMPLEXITY

- Complexity grows as log of size of one of its inputs
- Example algorithm: binary search of a list
- Example we'll see in a few slides: one bisection search implementation


## LIST AND DICTIONARIES

- Must be careful when using built-in functions!

Lists -n is len(L)

- index $\Theta(1)$
- store $\Theta(1)$
- length $\Theta(1)$
- append $\Theta(1)$
- ==
- remove
- copy
- reverse
- iteration
- in list
$\theta(n)$
$\theta(\mathrm{n})$
$\Theta(n)$
$\theta(n)$
$\theta(\mathrm{n})$

Dictionaries $\mathbf{- n}$ is len(d)

- index $\Theta(1)$
- store $\Theta(1)$
- length $\Theta(1)$
- delete $\Theta(1)$
- .keys $\quad \Theta(n)$
- .values $\Theta(n)$
- iteration $\Theta(n)$

$$
\begin{aligned}
& \text { SEARCHING } \\
& \text { ALGORITHMS }
\end{aligned}
$$

## SEARCHING ALGORITHMS

- Linear search
- Brute force search
- List does not have to be sorted
- Bisection search
- List MUST be sorted to give correct answer
- Will see two different implementations of the algorithm


## LINEAR SEARCH ON UNSORTED LIST

def linear_search(L, e):
found = False


- Must look through all elements to decide it's not there
- $\boldsymbol{O}$ (len(L)) for the loop * $\boldsymbol{O}(1)$ to test if $\mathrm{e}=\mathrm{L}[\mathrm{i}]$
- Overall complexity is $\Theta(n)$ where $n$ is len(L)
- O(len(L))


## LINEAR SEARCH ON UNSORTED LIST

$$
\begin{aligned}
& \text { def linear_search (L, e): } \\
& \begin{array}{c}
\text { for i in range(len(L)): } \\
\qquad \begin{array}{c}
\text { if } \begin{array}{c}
\text { }==\mathrm{L}[\mathrm{i}]: \\
\text { return True }
\end{array} \\
\hline
\end{array}
\end{array} \\
& \text { return False }
\end{aligned}
$$



- Must look through all elements to decide it's not there
- $\boldsymbol{O}(\operatorname{len}(\mathrm{L}))$ for the loop * $\boldsymbol{O}(1)$ to test if $\mathrm{e}=\mathrm{L}[\mathrm{i}]$
- Overall complexity is $\Theta(n)$ where $n$ is len(L)
- O(len(L))


## LINEAR SEARCH ON SORTED LIST

```
def search(L, e):
```

```
for i in L:
```

for i in L:
if i == e:

```
    if i == e:
```

        return True
    return False
    if i > e:
        return False
    o(1)
    - Must only look until reach a number greater than e
- $\Theta(\operatorname{len}(\mathrm{L}))$ for the loop * $\Theta(1)$ to test if $\mathrm{i}==\mathrm{e}$ or $\mathrm{i}>\mathrm{e}$
- Overall complexity is $\Theta(\operatorname{len}(\mathrm{L}))$
$\Theta(\mathrm{n})$ where n is $\operatorname{len}(\mathrm{L})$


## BISECTION SEARCH FOR AN ELEMENT IN A SORTED LIST

1) Pick an index, i, that divides list in half
2) Ask if L [i] == e
3) If not, ask if $L$ [ i ] is larger or smaller than e
4) Depending on answer, search left or right half of $L$ for $e$

- A new version of divide-and-conquer: recursion!
- Break into smaller versions of problem (smaller list), plus simple operations
- Answer to smaller version is answer to original version


## BISECTION SEARCH COMPLEXITY ANALYSIS



- Finish looking through list when $1=n / 2^{i}$
- So... relationship between original length of list and how many times we divide the list: $\mathrm{i}=\log \mathrm{n}$
- Complexity is O(log n) where $n$ is len(L)


## BlG IDEA

Two different implementations have two different $\Theta$ values.

## BISECTION SEARCH IMPLEMENTATION 1

def bisect_search1(L, e):


## COMPLEXITY OF bisect_search1 (where n is len(L))

- $\Theta(\log n)$ bisection search calls
- Each recursive call cuts range to search in half
- Worst case to reach range of size 1 from n is when $\mathrm{n} / 2^{\mathrm{k}}=1$ or when $\mathrm{k}=\log \mathrm{n}$
- We do this to get an expression relating $k$ to $n$
- $\boldsymbol{O}(\mathrm{n})$ for each bisection search call to copy list
- Cost to set up recursive call at each level of recursion
- $\Theta(\log n) * \Theta(n)=\Theta(n \log n)$ where $n=\operatorname{len}(L)$ $\wedge$ this is the answer in this class
- If careful, notice list is also halved on each recursive call
- Infinite series (don't worry about this in this class)
- $\Theta(n)$ is a tighter bound because copying list dominates log $n$


## BISECTION SEARCH ALTERNATE IMPLEMENTATION



- Reduce size of problem by factor of 2 each step
- Keep track of low and high indices to search list
- Avoid copying list
- Complexity of recursion is O(log n) where $n$ is $\operatorname{len}(\mathrm{L})$


## BISECTION SEARCH IMPLEMENTATION 2

def bisect_search2 (L, e):

def bisect_search_helper(L, e, low, high):
if high $==$ low:
return $L[$ low] $==e$
mid $=$ (low + high )//2
if L[mid] == e:
return True
elif L[mid] > e:
if low == mid: \#nothing left to search
return False
else:
return bisect_search_helper (L, e, low, mid - 1)
else:


## COMPLEXITY OF bisect_search2 and helper (where n is len(L))

- $\Theta(\log n)$ bisection search calls
- Each recursive call cuts range to search in half
- Worst case to reach range of size 1 from $n$ is when $n / 2^{k}=1$ or when $k=\log n$
- We do this to get an expression relating k to n
- Pass list and indices as parameters
- List never copied, just re-passed
- $\Theta(1)$ on each recursive call
- $\Theta(\log n)^{*} \Theta(1)=\Theta(\log n)$ where $n$ is len(L)


## WHEN TO SORT FIRST AND THEN SEARCH?

## SEARCHING A SORTED LIST -- n is len(L)

- Using linear search, search for an element is $\boldsymbol{O ( n )}$
- Using binary search, can search for an element in $\Theta(\log n)$
- Assumes the list is sorted!
- When does it make sense to sort first then search?

- When is sorting is less than $\Theta(\mathrm{n})$ ??!!?
$\rightarrow$ Never true because you'd at least have to look at each element!


## AMORTIZED COST <br> -- n is $\operatorname{len}(\mathrm{L})$

- Why bother sorting first?
- Sort a list once then do many searches
- AMORTIZE cost of the sort over many searches

- SORT $+\mathrm{K} * \Theta(\log \mathrm{n})<\mathrm{K} * \Theta(\mathrm{n})$
implies that for large $K$, SORT time becomes irrelevant


## COMPLEXITY CLASSES SUMMARY

- Compare efficiency of algorithms
- Lower order of growth
- Using $\Theta$ for an upper and lower ("tight") bound
- Given a function f:
- Only look at items in terms of the input
- Look at loops
- Are they in terms of the input to f?
- Are there nested loops?
- Look at recursive calls
- How deep does the function call stack go?
- Look at built-in functions
- Any of them depend on the input?

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