

# UNDERSTANDING PROGRAM EFFICIENCY

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# WANT TO UNDERSTAND EFFICIENCY OF PROGRAMS

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- computers are fast and getting faster – so maybe efficient programs don't matter?
  - but data sets can be very large
  - thus, simple solutions may simply not scale with size in acceptable manner
- so how could we decide which option for program is most efficient?
- separate **time and space efficiency** of a program
- tradeoff between them – will focus on time efficiency

# WANT TO UNDERSTAND EFFICIENCY OF PROGRAMS

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Challenges in understanding efficiency of solution to a computational problem:

- a program can be **implemented in many different ways**
- you can solve a problem using only a handful of different **algorithms**
- would like to separate choices of implementation from choices of more abstract algorithm

# HOW TO EVALUATE EFFICIENCY OF PROGRAMS

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- measure with a **timer**
- **count** the operations
- abstract notion of **order of growth**

will argue that this is the most appropriate way of assessing the impact of choices of algorithm in solving a problem; and in measuring the inherent difficulty in solving a problem

# TIMING A PROGRAM

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- use time module

- recall that importing means to bring in that class into your own file

```
import time
```

```
def c_to_f(c):  
    return c*9/5 + 32
```

- **start** clock

→ 

```
t0 = time.clock()
```

- **call** function

→ 

```
c_to_f(100000)
```






- **stop** clock

→ 

```
t1 = time.clock() - t0  
Print("t =", t, ":", t1, "s,")
```

# TIMING PROGRAMS IS INCONSISTENT

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- GOAL: to evaluate different algorithms
- running time **varies between algorithms** 
- running time **varies between implementations** 
- running time **varies between computers** 
- running time is **not predictable** based on small inputs 
- time varies for different inputs but cannot really express a relationship between inputs and time 

# COUNTING OPERATIONS

- assume these steps take

**constant time:**

- mathematical operations
  - comparisons
  - assignments
  - accessing objects in memory
- 
- then count the number of operations executed as function of size of input

```
def c_to_f(c):  
    return c*9.0/5 + 32
```

3 ops

```
def mysum(x):  
    total = 0  
    for i in range(x+1):  
        total += i  
    return total
```

1 op

loop x  
times

2 ops

1 op

mysum → 1+3x ops

# COUNTING OPERATIONS IS BETTER, BUT STILL...

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- GOAL: to evaluate different algorithms
- count **depends on algorithm** ✓
- count **depends on implementations** ✗
- count **independent of computers** ✓
- no real definition of **which operations** to count ✗
- count varies for different inputs and can come up with a relationship between inputs and the count ✓



# STILL NEED A BETTER WAY

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- timing and counting **evaluate implementations**
- timing **evaluates machines**
  
- want to **evaluate algorithm**
- want to **evaluate scalability**
- want to **evaluate in terms of input size**

# NEED TO CHOOSE WHICH INPUT TO USE TO EVALUATE A FUNCTION

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- want to express **efficiency in terms of input**, so need to decide what your input is
- could be an **integer**  
-- `mysum(x)`
- could be **length of list**  
-- `list_sum(L)`
- **you decide** when multiple parameters to a function  
-- `search_for_elmt(L, e)`

# DIFFERENT INPUTS CHANGE HOW THE PROGRAM RUNS

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- a function that searches for an element in a list

```
def search_for_elmt(L, e):  
    for i in L:  
        if i == e:  
            return True  
    return False
```

- when  $e$  is **first element** in the list → BEST CASE
- when  $e$  is **not in list** → WORST CASE
- when **look through about half** of the elements in list → AVERAGE CASE
- want to measure this behavior in a general way

# BEST, AVERAGE, WORST CASES

---

- suppose you are given a list  $L$  of some length  $\text{len}(L)$
- **best case**: minimum running time over all possible inputs of a given size,  $\text{len}(L)$ 
  - constant for `search_for_elmt`
  - first element in any list
- **average case**: average running time over all possible inputs of a given size,  $\text{len}(L)$ 
  - practical measure

*generally will  
focus on this case*

- **worst case**: maximum running time over all possible inputs of a given size,  $\text{len}(L)$ 
  - linear in length of list for `search_for_elmt`
  - must search entire list and not find it

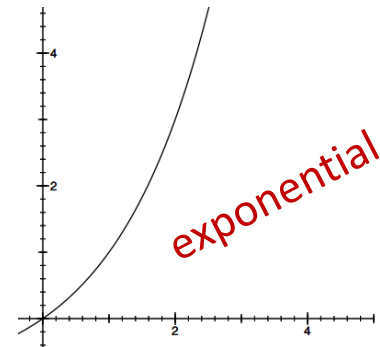
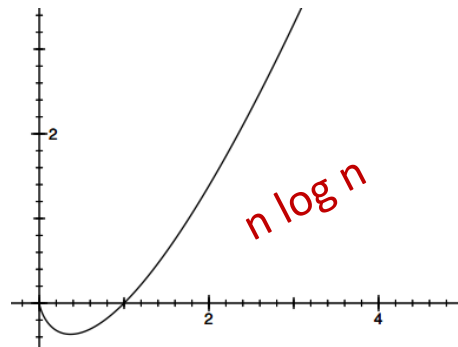
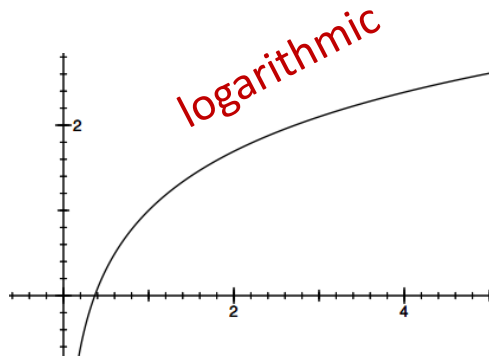
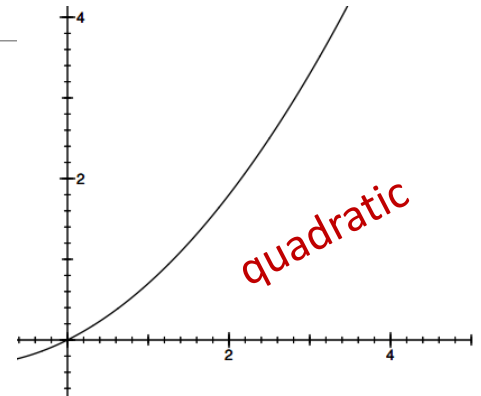
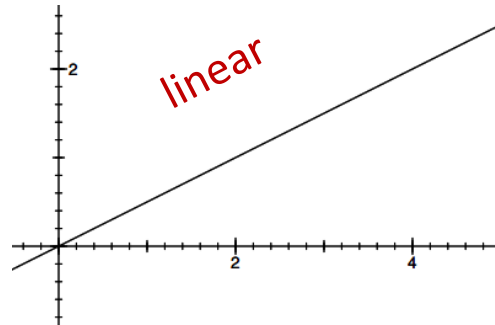
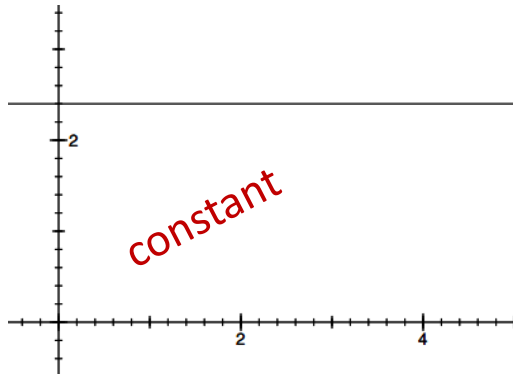
# ORDERS OF GROWTH

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## Goals:

- want to evaluate program's efficiency when **input is very big**
- want to express the **growth of program's run time** as input size grows
- want to put an **upper bound** on growth
- do not need to be precise: **"order of" not "exact"** growth
- we will look at **largest factors** in run time (which section of the program will take the longest to run?)

# TYPES OF ORDERS OF GROWTH



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# MEASURING ORDER OF GROWTH: BIG OH NOTATION

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- Big Oh notation measures an **upper bound on the asymptotic growth**, often called order of growth
- **Big Oh or  $O()$**  is used to describe worst case
  - worst case occurs often and is the bottleneck when a program runs
  - express rate of growth of program relative to the input size
  - evaluate algorithm not machine or implementation



# EXACT STEPS vs $O()$

---

```
def fact_iter(n):  
    """assumes n an int >= 0"""  
    answer = 1  
    while n > 1:  
        answer *= n  
        n -= 1  
    return answer
```

*temp = n-1  
n = temp*

- computes factorial
- number of steps:  *$1 + 5n + 1$*
- worst case asymptotic complexity:  *$O(n)$* 
  - ignore additive constants
  - ignore multiplicative constants

# SIMPLIFICATION EXAMPLES

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- drop constants and multiplicative factors
- focus on **dominant terms**

$$O(n^2) : n^2 + 2n + 2$$

$$O(n^2) : n^2 + 100000n + 3^{1000}$$

$$O(n) : \log(n) + n + 4$$

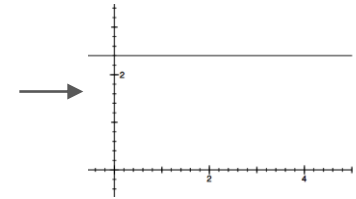
$$O(n \log n) : 0.0001 * n * \log(n) + 300n$$

$$O(3^n) : 2n^{30} + 3^n$$

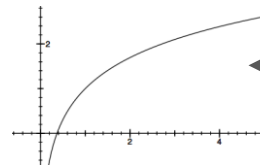
# COMPLEXITY CLASSES ORDERED LOW TO HIGH

more efficient:  $O(1)$  :

constant



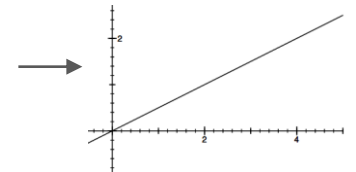
$O(\log n)$  :



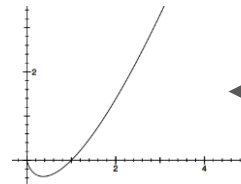
← logarithmic

$O(n)$  :

linear



$O(n \log n)$  :



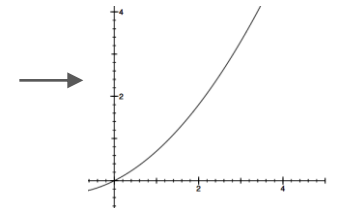
← loglinear

less efficient:

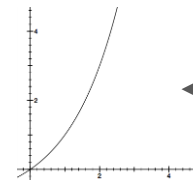
*c is a  
constant*

$O(n^c)$  :

polynomial →



$O(c^n)$  :



← exponential

# ANALYZING PROGRAMS AND THEIR COMPLEXITY

---

- **combine** complexity classes
  - analyze statements inside functions
  - apply some rules, focus on dominant term

## **Law of Addition** for $O()$ :

- used with **sequential** statements
- $O(f(n)) + O(g(n))$  is  $O(f(n) + g(n))$
- for example,

```
for i in range(n):  
    print('a')  
for j in range(n*n):  
    print('b')
```

is  $O(n) + O(n*n) = O(n+n^2) = O(n^2)$  because of dominant term

# ANALYZING PROGRAMS AND THEIR COMPLEXITY

---

- **combine** complexity classes
  - analyze statements inside functions
  - apply some rules, focus on dominant term

## **Law of Multiplication** for $O()$ :

- used with **nested** statements/loops
- $O(f(n)) * O(g(n))$  is  $O(f(n) * g(n))$
- for example,

```
for i in range(n):  
    for j in range(n):  
        print('a')
```

is  $O(n) * O(n) = O(n * n) = O(n^2)$  because the outer loop goes  $n$  times and the inner loop goes  $n$  times for every outer loop iter.

---

# COMPLEXITY CLASSES

---

- $O(1)$  denotes constant running time
- $O(\log n)$  denotes logarithmic running time
- $O(n)$  denotes linear running time
- $O(n \log n)$  denotes log-linear running time
- $O(n^c)$  denotes polynomial running time ( $c$  is a constant)
- $O(c^n)$  denotes exponential running time ( $c$  is a constant being raised to a power based on size of input)

# CONSTANT COMPLEXITY

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- 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



# LOGARITHMIC COMPLEXITY

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- complexity grows as log of size of one of its inputs
- example:
  - bisection search
  - binary search of a list

# LOGARITHMIC COMPLEXITY

---

```
def intToStr(i):  
    digits = '0123456789'  
    if i == 0:  
        return '0'  
    result = ''  
    while i > 0:  
        result = digits[i%10] + result  
        i = i//10  
    return result
```

# LOGARITHMIC COMPLEXITY

---

```
def intToStr(i):  
    digits = '0123456789'  
    if i == 0:  
        return '0'  
    res = ''  
    while i > 0:  
        res = digits[i%10] + res  
        i = i//10  
    return res
```

only have to look at loop as  
no function calls

within while loop, constant  
number of steps

how many times through  
loop?

- how many times can one  
divide  $i$  by 10?
- $O(\log(i))$

# LINEAR COMPLEXITY

---

- searching a list in sequence to see if an element is present
- add characters of a string, assumed to be composed of decimal digits

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

- $O(\text{len}(s))$

# LINEAR COMPLEXITY

---

- complexity can depend on number of recursive calls

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

- number of times around loop is  $n$
- number of operations inside loop is a constant
- overall just  $O(n)$

# O() FOR RECURSIVE FACTORIAL

---

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

- computes factorial recursively
- if you time it, may notice that it runs a bit slower than iterative version due to function calls
- still **O(n)** because the number of function calls is linear in n
- **iterative and recursive factorial** implementations are the **same order of growth**

# LOG-LINEAR COMPLEITY

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- many practical algorithms are log-linear
- very commonly used log-linear algorithm is merge sort
- will return to this

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# POLYNOMIAL COMPLEXITY

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- 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

---

```
def isSubset(L1, L2):  
    for e1 in L1:  
        matched = False  
        for e2 in L2:  
            if e1 == e2:  
                matched = True  
                break  
        if not matched:  
            return False  
    return True
```

# QUADRATIC COMPLEXITY

---

```
def isSubset(L1, L2):  
    for e1 in L1:  
        matched = False  
        for e2 in L2:  
            if e1 == e2:  
                matched = True  
                break  
        if not matched:  
            return False  
    return True
```

outer loop executed  $\text{len}(L1)$  times

each iteration will execute inner loop up to  $\text{len}(L2)$  times

$O(\text{len}(L1) * \text{len}(L2))$

worst case when  $L1$  and  $L2$  same length, none of elements of  $L1$  in  $L2$

$O(\text{len}(L1)^2)$

# QUADRATIC COMPLEXITY

---

find intersection of two lists, return a list with each element appearing only once

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

# QUADRATIC COMPLEXITY

---

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

first nested loop takes  
 $\text{len}(L1) * \text{len}(L2)$  steps

second loop takes at  
most  $\text{len}(L1)$  steps

latter term  
overwhelmed by  
former term

$O(\text{len}(L1) * \text{len}(L2))$

# O() FOR NESTED LOOPS

---

```
def g(n) :  
    """ assume n >= 0 """  
    x = 0  
    for i in range(n) :  
        for j in range(n) :  
            x += 1  
    return x
```

- computes  $n^2$  very inefficiently
- when dealing with nested loops, **look at the ranges**
- nested loops, **each iterating n times**
- **$O(n^2)$**

---

# EXPONENTIAL COMPLEXITY

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- recursive functions where more than one recursive call for each size of problem
  - Towers of Hanoi
- many important problems are inherently exponential
  - unfortunate, as cost can be high
  - will lead us to consider approximate solutions more quickly



# EXPONENTIAL COMPLEXITY

---

```
def genSubsets (L) :  
    res = []  
    if len(L) == 0:  
        return [[]] #list of empty list  
    smaller = genSubsets(L[:-1]) # all subsets without  
last element  
    extra = L[-1:] # create a list of just last element  
    new = []  
    for small in smaller:  
        new.append(small+extra) # for all smaller  
solutions, add one with last element  
    return smaller+new # combine those with last  
element and those without
```

# EXPONENTIAL COMPLEXITY

---

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

assuming append is  
constant time

time includes time to solve  
smaller problem, plus time  
needed to make a copy of  
all elements in smaller  
problem

# EXPONENTIAL COMPLEXITY

---

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

but important to think  
about size of smaller

know that for a set of size  
k there are  $2^k$  cases

so to solve need  $2^{n-1} + 2^{n-2}$   
+ ... +  $2^0$  steps

math tells us this is  $O(2^n)$

# COMPLEXITY CLASSES

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- $O(1)$  denotes constant running time
- $O(\log n)$  denotes logarithmic running time
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- $O(n \log n)$  denotes log-linear running time
- $O(n^c)$  denotes polynomial running time ( $c$  is a constant)
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# EXAMPLES OF ANALYZING COMPLEXITY

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# TRICKY COMPLEXITY

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```
def h(n):  
    """ assume n an int >= 0 """  
    answer = 0  
    s = str(n)  
    for c in s:  
        answer += int(c)  
    return answer
```

linear  $O(\text{len}(s))$   
but what in terms  
of input  $n$ ?

- adds digits of a number together
- tricky part
  - convert integer to string
  - iterate over **length of string**, not magnitude of input  $n$
  - think of it like dividing  $n$  by 10 each iteration
- **$O(\log n)$**  – base doesn't matter

# COMPLEXITY OF ITERATIVE FIBONACCI

```
def fib_iter(n):
```

```
    if n == 0:
```

```
        return 0
```

```
    elif n == 1:
```

```
        return 1
```

```
    else:
```

```
        fib_i = 0
```

```
        fib_ii = 1
```

```
        for i in range(n-1):
```

```
            tmp = fib_i
```

```
            fib_i = fib_ii
```

```
            fib_ii = tmp + fib_i
```

```
        return fib_ii
```

constant  
 $O(1)$

constant  
 $O(1)$

linear  
 $O(n)$

constant  
 $O(1)$

- Best case:

$O(1)$

- Worst case:

$O(1) + O(n) + O(1) \rightarrow \mathbf{O(n)}$

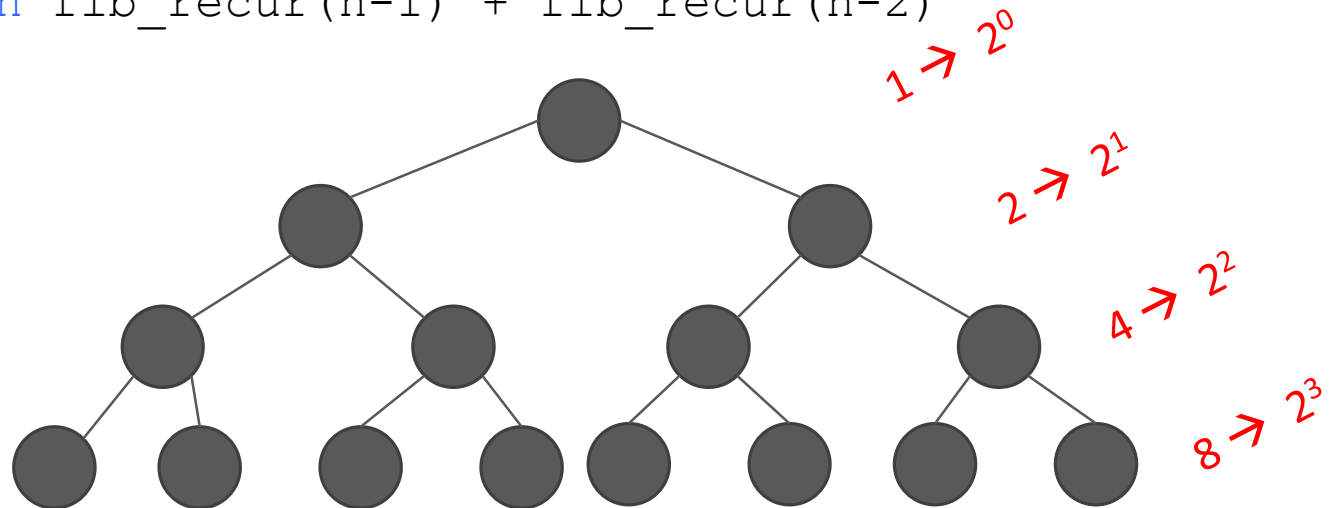


# COMPLEXITY OF RECURSIVE FIBONACCI

```
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:

**$O(2^n)$**



# WHEN THE INPUT IS A LIST...

---

```
def sum_list(L):  
    total = 0  
    for e in L:  
        total = total + e  
    return total
```

- $O(n)$  where  $n$  is the length of the list
- $O(\text{len}(L))$
- must **define what size of input means**
  - previously it was the magnitude of a number
  - here, it is the length of list

# BIG OH SUMMARY

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- compare **efficiency of algorithms**
  - notation that describes growth
  - **lower order of growth** is better
  - independent of machine or specific implementation
- use Big Oh
  - describe order of growth
  - **asymptotic notation**
  - **upper bound**
  - **worst case** analysis

# COMPLEXITY OF COMMON PYTHON FUNCTIONS

---

## ■ Lists: $n$ is `len(L)`

- index  $O(1)$
- store  $O(1)$
- length  $O(1)$
- append  $O(1)$
- `==`  $O(n)$
- remove  $O(n)$
- copy  $O(n)$
- reverse  $O(n)$
- iteration  $O(n)$
- in list  $O(n)$

## ■ Dictionaries: $n$ is `len(d)`

### ■ worst case

- index  $O(n)$
- store  $O(n)$
- length  $O(n)$
- delete  $O(n)$
- iteration  $O(n)$

### ■ average case

- index  $O(1)$
- store  $O(1)$
- delete  $O(1)$
- iteration  $O(n)$