# LIST ACCESS, HASHING, SIMULATIONS, \& WRAP-UP! 

(download slides and .py files to follow along)

### 6.100L Lecture 26

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## TODAY

- A bit about lists
- Hashing
- Simulations


## LISTS

## COMPLEXITY OF SOME PYTHON OPERATIONS

- Lists: n is len (L)
- access $\theta(1)$
- store $\theta(1)$
- length $\theta(1)$
- append $\theta(1)$
- == $\quad \theta(n)$
- delete $\theta(n)$
- copy $\theta(n)$
- reverse $\boldsymbol{\theta}(\mathrm{n})$
- iteration $\theta(n)$
- in list $\boldsymbol{\theta}(\mathrm{n})$


## CONSTANT TIME LIST ACCESS



- Store values directly
- Consecutive set of memory locations
- List name points to first memory location
- To access ith element
- Add 32*i to first location
- Access that location in memory
- Constant time complexity


## CONSTANT TIME LIST ACCESS

- If list is heterogeneous
- Can't store values directly (don't all fit in 32 bits)
- Use indirection to reference other objects
- Store pointers to values (not value itself)
- Still use consecutive set of memory locations
- Still set aside 4 *en(L) bytes
- Still add $32 *$ i to first location and +1 to access that location in memory
- Still constant time complexity



## NAÏVE IMPLEMENTATION OF dict

- Just use a list of pairs: key, value
[['Ana', True], ['John', False], ['Eric', False], ['Sam', False]]
- What is time complexity to index into this naïve dictionary?
- We don't know the order of entries
- Have to do linear search to find entry


## COMPLEXITY OF SOME PYTHON OPERATIONS

| - Lists: n | is $\operatorname{len}(\mathrm{L})$ |
| :--- | :--- |
| - access | $\theta(1)$ |
| - store | $\theta(1)$ |
| - length | $\theta(1)$ |
| - append | $\theta(1)$ |
| - == | $\theta(\mathbf{n})$ |
| - delete | $\theta(\mathbf{n})$ |
| - copy | $\theta(\mathbf{n})$ |
| - reverse | $\theta(\mathbf{n})$ |
| - iteration | $\theta(\mathbf{n})$ |
| - in list | $\boldsymbol{\theta ( n )}$ |

- Dictionaries: n is len(d)
- worst case (very rare)
- length $\theta(\mathrm{n})$
- access $\theta(n)$
- store $\theta(n)$
- delete $\theta(n)$
- iteration $\theta(n)$
- average case
- access $\theta(1)$
- store $\theta(1)$
- delete $\theta(1)$
- in $\theta(1)$
- iteration $\theta(n)$


## HASHING

## DICTIONARY IMPLEMENTATION

- Uses a hash table
- How it does it
- Convert key to an integer - use a hash function
- Use that integer as the index into a list
- This is constant time
- Find value associated with key
- This is constant time
- Dictionary lookup is constant time complexity
- If hash function is fast enough
- If indexing into list is constant


## QUERYING THE HASH FUNCTION

- Just to reveal what's under the hood, a function hash ()

```
In [9]: hash(123)
Out[9]: 123
In [10]: hash("6.100L is awesome")
Out[10]: 8708784260240907980
In [11]: hash( \((1,2,3))\)
Out[11]: 529344067295497451
In [12]: hash([1, 2, 3])
Traceback (most recent call last):
```

May vary because Python adds
randomness to thwart attacks
Why do this? Because hashing
is also used to encrypt data for is also used to encrypt data safe storage an

```
    File "<ipython-input-12-35e31e935e9e>",
line 1, in <module>
    hash([1, 2, 3])
```

TypeError: unhashable type: 'list'

## HASH TABLE

- How big should a hash table be?
- To avoid many keys hashing to the same value, have each key hash to a separate value
- If hashing strings:
- Represent each character with binary code
- Concatenate bits together, and convert to an integer


## NAMES TO INDICES

- E.g., 'Ana Bell'
$=0100000101101110011000010010000001000010011001010110110001101100$
$=4,714,812,651,084,278,892$
- Advantage: unique names mapped to unique indices
- Disadvantage: VERY space inefficient
- Consider a table containing MIT’s ~4,000 undergraduates
- Assume longest name is 20 characters
- Each character 8 bits, so 160 bits per name
- How many entries will table have?


## A BETTER IDEA: ALLOW COLLISIONS

Hash function:

1) Sum the letters
2) Take mod 16 (to fit in a hash table with 16 entries)


## Hash table (like a list)



## PROPERTIES OF A GOOD HASH FUNCTION

- Maps domain of interest to integers between 0 and size of hash table
- The hash value is fully determined by value being hashed (nothing random)
- The hash function uses the entire input to be hashed
- Fewer collisions
- Distribution of values is uniform, i.e., equally likely to land on any entry in hash table
- Side Reminder: keys in a dictionary must be hashable
- aka immutable
- They always hash to the same value
- What happens if they are not hashable?

Hash function:

1) Sum the letters
2) Take mod 16 (to fit in a memory block with 16 entries)
$1+14+1=16$
$16 \% 16=0$


## Hash table (like a list)

| 0 |
| :---: |
| 1 |
| 2 |
| 3 |
| 4 |
| 5 |
| 6 |
| 7 |
| 8 |
| 9 |
| 10 |
| 11 |
| 12 |
| 13 |
| 14 |
| 15 |

Eric: A
$[K, a, t, e]: B$

John: B

Hash function:

1) Sum the letters
2) Take mod 16 (to fit in a memory block with 16 entries)

Kate changes her name to Cate. Same person, different name. Look up her grade?

## Hash table (like a list)

| 0 |
| :---: |
| 1 |
| 2 |
| 3 |
| 4 |
| 5 |
| 6 |
| 7 |
| 8 |
| 9 |
| 10 |
| 11 |
| 12 |
| 13 |
| 14 |
| 15 |

Ana: C Eve: B

Eric: A
[K,a,t,e]: B
$\leftarrow$ ??? Not here!

John: B

## COMPLEXITY OF SOME PYTHON OPERATIONS

- Dictionaries: n is len (d)
- worst case (very rare)
- length $\theta(n)$
- access $\theta(n)$

If all keys hash to the same index

- store $\theta(\mathrm{n})$
- delete $\theta(\mathrm{n})$
- iteration $\boldsymbol{\theta}(\mathrm{n})$
- average case
- access $\theta(1)$
- store $\theta(1)$
- delete $\theta(1)$
- in $\theta(1)$

Hash table is large relative to

- iteration $\boldsymbol{\theta}(\mathrm{n})$


## SIMULATIONS

## TOPIC USEFUL FOR MANY DOMAINS

- Computationally describe the world using randomness
- One very important topic relevant to many fields of study
- Risk modeling and analysis
- Reduce complex models
- Idea:
- Observe an event and want to calculate something about it
- Using computation, design an experiment of that event
- Repeat the experiment K many times (make a simulation)
- Keep track of the outcome of your event
- After K repetitions, report the value of interest


## ROLLING A DICE

- Observe an event and want to calculate something about it
- Roll a dice, what's the prob to get a ::? How about a .?
- Using computation, design an experiment of that event
- Make a list representing die faces and randomly choose one
" random.choice(['.',':',':.','::','::.',':::'])
- Repeat the experiment K many times (simulate it!)
- Randomly choose a die face from a list repeatedly, 10000 times
- How? Wrap the simulation in a loop!
for i in range(10000):
roll=random.choice(['.',':',':.','::','::.',':::'])
- Keep track of the outcome of your event
- Count how many times out of 10000 the roll equaled ::
- After K repetitions, report the value of interest
- Divide the count by 10000


## THE SIMULATION CODE

```
def prob_dice(side):
```



```
    print(count/Nsims)
prob_dice('.')
```


## THAT'S AN EASY SIMULATION

- We can compute the probability of a die roll mathematically
- Why bother with the code?
- Because we can answer variations of that original question and we can ask harder questions!
- Small tweaks in code
- Easy to change the code
- Fast to run


## NEW QUESTION <br> NOT AS EASY MATHEMATICALLY

- Observe an event and want to calculate something about it
- Roll a dice 7 times, what's the prob to get a :: at least 3 times out of 7 rolls?
- Using computation, design an experiment of that event
- Make a list representing die faces and randomly choose one 7 times in a row
- Face counter increments when you choose :: (keep track of this number)
- Repeat the experiment K many times (simulate it!)
- Repeat the prev step 10000 times.
- How? Wrap the simulation in a loop!
- Keep track of the outcome of your event
- Count how many times out of 10000 the :: face counter >= 3
- After K repetitions, report the value of interest
- Divide the outcome count by 10000


## EASY TWEAK TO EXISTING CODE

```
def prob_dice_atleast(Nrolls, n_at_least):
```

    dice \(=\) ['.',':',':.',': ' ',': .',': : '']
    Nsims \(=10000\)
    how_many_matched = []
    for i in range(Nsims):
    ```
matched = 0
for i in range(Nrolls):
                    roll = random.choice(dice)
                    if roll == '::':
                        matched += 1
how_many_matched.append (matched)
```

```
count = 0
for i in how_many_matched:
    if i >= n_at_least:
        count += 1
```


print(count/len(how_many_matched))

| prob_dice_atleast $(7,3)$ | 0.0955 |
| :--- | :--- |
| prob_dice_atleast $(1, ~ 1)$ | $0.16{ }_{26}$ |

## REAL WORLD QUESTION <br> VERY COMMON EXAMPLE OF HOW USEFUL SIMULATIONS CAN BE

- Water runs through a faucet somewhere between 1 gallons per minute and 3 gallons per minute
- What's the time it takes to fill a 600 gallon pool?
- Intuition?
- It's not 300 minutes (600/2)
- It's not 400 minutes $(600 / 1+600 / 3) / 2$
- In code:
- Grab a bunch of random values between 1 and 3
- Simulate the time it takes to fill a 600 gallon pool with each randomly chose value
- Print the average time it takes to fill the pool over all these randomly chosen values

```
def fill_pool(size):
    flow_rate = []
    fill_time = []
    Npoints = 10000
    for i in range Npoints):
    Numonen}\mathrm{ flow_rate.append(r)
    print('avg flow_rate:', Sum(flow_rate)/len(flow_rate))
    print('avg fill_time', sum(fill time)/len(fill time))
    plt.figure()
    plt.scatter(range(Npoints),flow_rate,s=1)
    plt.figure()
    plt.scatter(range(Npoints),fill_time,s=1)
```

fill_pool(600)

# PLOTTING RANDOM FILL RATES AND CORRESPONDING TIME IT TAKES TO FILL 

Random values for fill rate


Time to fill using formula pool_size/rate


## PLOTTING RANDOM FILL RATES AND CORRESPONDING TIME IT TAKES TO FILL

Random values for fill rate (sorted)


Time to fill (sorted) using formula pool_size/rate


## RESULTS

- avg flow_rate:
- avg fill_time:
1.992586945871106 approx. 2 gal/min (avg random values between 1 and 3) 330.6879477596955 approx. 331 min (not what we expected!)
- Not 300 and not 400
- There is an inverse relationship for fill time vs fill rate
- Mathematically you'd have to do an integral
- Computationally you just write a few lines of code!


# WRAP-UP of 6.100L 

THANK YOU FOR BEING IN THIS CLASS!

## WHAT DID YOU LEARN?

- Python syntax
- Flow of control
- Loops, branching, exceptions
- Data structures
- Tuples, lists, dictionaries
- Organization, decomposition, abstraction
- Functions
- Classes
- Algorithms
- Binary/bisection
- Computational complexity
- Big Theta notation
- Searching and sorting


## YOUR EXPERIENCE

- Were you a "natural"?
- Did you join the class late?
- Did you work hard?
- Look back at the first pset it will seem so easy!
- You learned a LOT no matter what!


## WHAT'S NEXT

- 6.100B overview of interesting topics in CS and data science (Python)
- Optimization problems
- Simulations
- Experimental data
- Machine learning


## WHAT'S NEXT

- 6.101 fundamentals of programming (Python)
- Implementing efficient algorithms
- Debugging


## WHAT'S NEXT

- 6.102 software construction (TypeScript)
- Writing code that is safe from bugs, easy to understand, ready for change


## WHAT'S NEXT

- Other classes
(ML, algorithms, etc.)


## IT'S EASY TO FORGET WITHOUT PRACTICE! HAPPY CODING!

MITOpenCourseWare
https://ocw.mit.edu

### 6.100L Introduction to Computer Science and Programming Using Python Fall 2022

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