## Extended Introduction to Computer Science CS1001.py

Chapter G Data Structures 3:

Lecture 16 Hash Functions and Hash Tables

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<sup>\*</sup> Slides based on a course designed by Prof. Benny Chor

#### Data Structures

1. Linked Lists



2. Binary Search Trees



3. Hash tables



4. Generators

#### Lecture Plan

Hash functions

- Hash tables
  - Allow insert, delete, search in O(1) time "on average"
  - Collisions and resolving them with chaining
  - class Hashtable

#### "Hash"?

Definition (from the Merriam-Webster dictionary):

hash - transitive verb

1 a: to chop (as meat and potatoes) into small pieces

b: confuse, muddle

2 : to talk about: review -- often used with over or out

**Synonyms**: dice, chop, mince

Antonyms: arrange, array, dispose, draw up, marshal (also marshall), order, organize, range,

regulate, straighten (up), tidy

- In computer science, hashing has multiple meanings, often unrelated.
  - For example, universal hashing, perfect hashing, cryptographic hashing, and geometric hashing, have very different meanings.

- Common to all of them is a mapping from a large space into a smaller one.
- Today, we will study hashing in the context of hash tables

#### **Hash Functions**

- Hash function: a function that maps a large (possibly infinite) set to a smaller set of a fixed size.
- Example for a hash function from integers to integers:

```
def hash4int(n):
    m = 1000
    c = (5**0.5-1)/2 #some irrational, 0<c<1
    return int(m*((n*c)%1))</pre>
```

- Executions in class
- Note that this function spreads the (infinite) set of integers over a small finite range (0-999).
- But what can such a function be possibly good for? soon...

### Hash Functions (cont.)

- Hash function: a function that maps a large (possible infinite) set to a smaller set of a fixed size.
- Example for a hash function from strings to integers:

```
def hash4strings(st):
    p = 2**120+451 # some arbitrary prime number
    x = 128
    s = 0
    for c in st:
        s = (x*s + ord(c)) % p
    return s
```

- Note that this function spreads the (infinite) set of strings over a finite range (0...p-1).
- But what can such a function be possibly good for? soon...

### Python's Built-in hash Function

 Python comes with its own hash function, from any immutable type to integers (both negative and positive):

```
>>> hash("Michal")
5551611717038549197
>>> hash("Amir")
-6654385622067491745
>>> hash((3,4))
3713083796997400956
>>> hash([3,4])
Traceback (most recent call last):
    File "<pyshell #16 >", line 1, in <module >
          hash([3,4])
TypeError: unhashable type: 'list'
```

But what can such a function be possibly good for? soon...

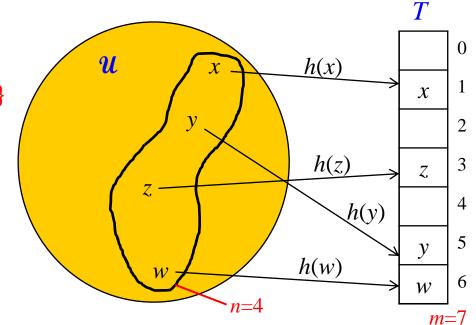
## Hashing with a Random Seed

- If you run this code yourself, you will probably encounter different outputs from those in the last slide
- This is because when IDLE starts, it randomly generates a number called seed, which is used to compute the built-in hash function
  - This is intended to provide protection against denial-of-service attacks caused by carefully-chosen inputs, designed to exploit a worst-case scenarios (which will be explained and analyzed soon).
- But as long as you work under the same instance of IDLE, hash is consistent and deterministic. So, consistency is kept for the lifetime of an IDLE session

#### Hash Tables: Definition

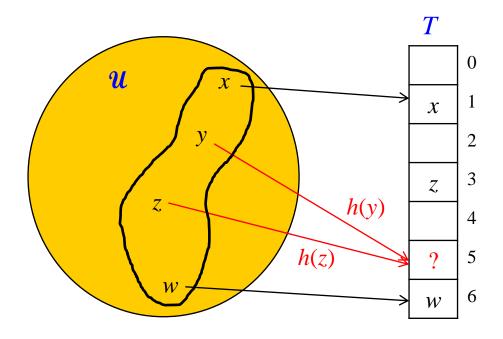
- Suppose elements belong to a large set (possibly infinite), called the "universe", denoted  ${\it u}$ 
  - for example: all possible ID numbers, all possible strings, etc.
- We need to store some n elements from u, and n << |u|.
  - for example: ID's of students in class right now, genes of a specific organism
- We store the elements in a table T called hash table, whose size is  $m \approx n$ .
- To map elements from  ${\it u}$  to  ${\it T}$  we use a hash function  $h\colon {\it u} \to \{0,1,...,m-1\}$  For example:  $h={\rm hash}\,({\rm key})\,{\rm m}$

Element with key  $k \in \mathcal{U}$  is stored (and searched for) at index h(k) in T.



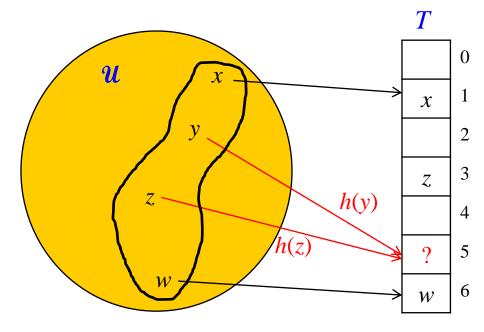
#### Problem

 Handle collisions while providing efficient insert, delete, search



#### Collisions

• Collision:  $h(k_1) = h(k_2)$  for  $k_1 \neq k_2$ 



Can we totally avoid collisions?

#### <u>Pigeonhole principle</u>:

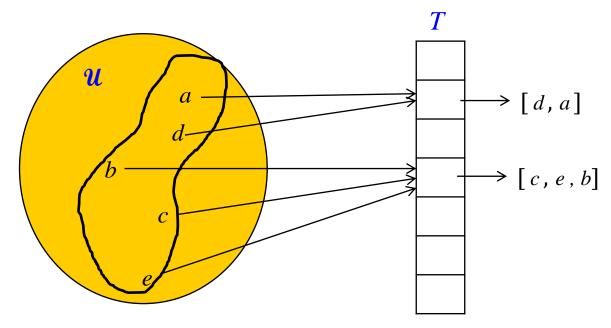
if n+1 pigeons enter n holes,
 at least 1 hole will contain at least 2 pigeons



- How can we decrease the probability for collisions?
  - Larger T
  - "Better" *h* (more on that soon)

#### Dealing with Collisions: Chaining Method

- Each cell in the table will contain a chain with all the current elements that h maps to this cell
- The chains can be implemented using Python's lists or linked lists



How do we insert, search and delete elements?

### Simple (interactive) Example for ID's

We want to store all students who attended class today, by their ID.

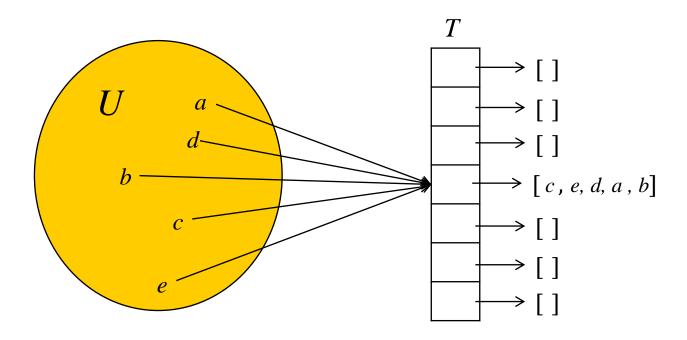
- $u = \{ \text{all possible Israeli ID numbers } \}$ |u| = ?
- n=?
- |T| = m = 10
- (m=10)h(id) = id % m0 h(id) = id%m3 → [] 5 → [] 6 8

### Implementing Insert, Delete, Search

- Initialization: create a table T with m empty lists
- Given an element with key  $k \in \mathcal{U}$ :
  - Search: compute i = h(k) and check if chain T[i] contains the key k.
  - Insert: compute i = h(k)if k not in the chain T[i], insert element to chain T[i]. otherwise? replace element or make no change.
  - <u>Delete</u>: compute i = h(k)if k in chain T[i], remove element from chain T[i].

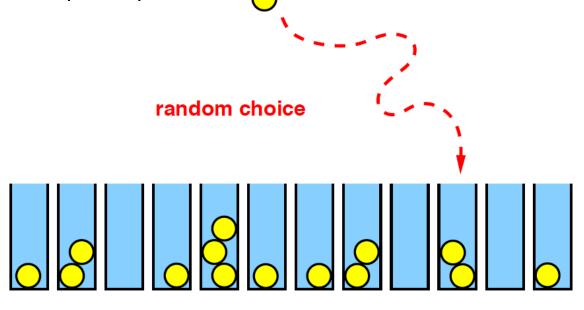
#### Chaining – Time Complexity: Worst Case

- In each operation we compute h(k) and then iterate over a single chain
- The worst-case time complexity, for the three operations search, insert and delete in terms of n is O(n).
  - This happens when all the elements inserted were hashed to the same single cell
  - Assumption: computing h and comparing 2 elements both take O(1) time



#### Chaining – Time Complexity: Average

- The worst case may indeed occur. But assuming h was chosen carefully and spreads elements rather uniformly and independently, the worst case is very rare!
  - The definitions of "uniformly" and "independently" will be taught in a probability course.
  - The scenario is often described as throwing n balls into m bins. The distribution of balls in the bins (maximum load, number of empty bins, etc.) is a well studied topic in probability theory.



The figure is taken from a manuscript titled "Balls and Bins -- A Tutorial", by Berthold Vöcking (Universität Dortmund).

#### Chaining – Time Complexity: Average

- Assuming h indeed "spreads elements well", as mentioned above, it
  makes sense to measure complexity in terms of the average length of
  a chain (average over the distribution of elements in the table).
- Average chain length is  $\alpha = \frac{n}{m}$  ( $\alpha$  is termed the load factor).
- If we choose m (table size) such that n = O(m), then  $\alpha = O(1)$ .
- Therefore, all operations run in O(1) "on average"
- Note: assuring n = O(m) requires prior estimation of the number of elements n we expect to be inserted into the table, or a mechanism to dynamically update the table size m

#### Time – Space Tradeoff

• We don't want  $\alpha$  to be neither too large (why?) nor too small (why?)

#### "Good" Hash Functions?

- You may wonder what it practically means to choose h "carefully".
- Is h(id) = id%100 a good hash function for id's?
- When we have some apriori knowledge on the keys, their distribution and properties, etc., we can tailor a specific hash function, that will improve spread-out among table cells.
- However, such knowledge is not always at hand. In addition, as we mentioned, choosing h at random once in a while is a rather good idea.
  - In the data structure course you will define a mechanism called universal families to solve both problems
- Practically, we can expect Python's hash to do a good job.

### Python's dict and set

- Python's class dict and class set are both implemented behind the scenes as hash tables.
- This explains why they are such good choices for storing and searching elements. Indeed, we used them (rather than lists for example) for memoization.
- dict and set however do not use chaining to solve collisions. They
  use another approach called open addressing (more later and in the
  data structures course)
- In addition, dict and set are dynamic hash tables they expand and shrink as the load factor becomes too large or too small, respectively.
- The exact details may change between Python versions, due to optimization efforts by the language developers. We will not delve into
   those details.

### Hash-ability and Immutability

- Recall class dict allows only immutable keys, and class set allows only immutable members.
- Indeed, hashing mutable objects is highly problematic.
- Suppose we insert a mutable object into a hashtable (or set or dict), then we mutate the object. If the mutated object hash a different hash value, then it is now located at the wrong position in the hash table, and we will not be able to find it.
- With immutable objects, this cannot happen.

#### Comic Relief\*

#### 1st rule of Programming:

If it works .... don't touch it!..



### Implementation in Python

Let us implement our own class Hashtable in Python now.

 We will assume elements have only keys, so we are actually implementing something that resembles Python's sets.

- However, as opposed to Python sets,
  - 1) We will use chaining to resolve collisions.
  - 2) Our table size will be defined at initialization and the table will not be dynamic.

### Initializing the Hash Table

```
class Hashtable:
def init (self, m, hash func=hash):
    """ initial hash table, m empty entries """
    self.table = [[] for i in range(m)]
    self.hash mod = lambda key: hash func(key) % m
def repr (self):
    return "".join([str(i) + " " + str(self.table[i]) + "\n"
                      for i in range(len(self.table))])
```

## Initializing the Hash Table

```
>>> ht = Hashtable(11)
>>> ht
 []
5 []
10 []
```

#### Initializing the Hash Table: a Bogus Code

Consider the following alternative initialization:

```
class Hashtable:
    def __init__(self, m, hash_func=hash):
        """ initial hash table, m empty entries """
        self.table = [[]]*m
```

```
>>> ht = Hashtable(11)
>>> ht.table[0].append(5)
>>> ht
0 [5]
1 [5]
...
>>> ht.table[0] == ht.table[1]
True
>>> ht.table[0] is ht.table[1]
True
```

The entries produced by this bogus \_\_init\_\_ are identical. Therefore, mutating one mutate all of them.

#### Dictionary Operations: Python Code

```
class Hashtable:
    def contains (self, item):
        """ returns True if item in hashtable, False otherwise
            Used by the 'in' operator in Python """
        i = self.hash mod(item)
        chain = self.table[i]
        if item in chain: # calls contains of Python's list
              return True
        else:
            return False
                                             return item in chain
   def insert(self, item):
        """ insert an item into table, if not there """
        i = self.hash mod(item)
        chain = self.table[i]
        if item not in chain:
            chain.append(item)
```

# Example: A Very Small Table (n = 14, m = 7)

- In the following slides, there are executions that construct a hash table with m=7 entries. We'll insert n=14 string records in it and check how insertions are distributed, and in particular what the maximum number of collisions per cell is.
- Our hash table will be a list with m = 7 entries. Each entry will contain a list with a variable length. Initially, each entry of the hash table is an empty list.

## Example: A Very Small Table (n = 14, m = 7)

```
>>> tribes = ['Reuben', 'Simeon', 'Levi', 'Judah', 'Dan', 'Naphtali',
  'Gad', 'Asher', 'Issachar', 'Zebulun', 'Benjamin', 'Joseph',
  'Ephraim', 'Manasse']
>>> ht = Hashtable(7) # calls init
>>> for name in tribes:
       ht.insert(name)
>>> 'Reuben' in ht # calls contains
True
>>> 'reuben' in ht # calls contains
False
>>> ht # calls repr
      (next slide)
```

## Example: A Very Small Table (n = 14, m = 7)

```
>>> ht # calls __repr__
0 []
1 ['Reuben', 'Judah', 'Dan']
2 ['Naphtali']
3 ['Gad', 'Ephraim']
4 ['Levi']
5 ['Issachar', 'Zebulun']
6 ['Simeon', 'Asher', 'Benjamin', 'Joseph', 'Manasse']
```

## Example: A slightly larger table (n = 14, m = 21)

```
>>> tribes = ['Reuben', 'Simeon', 'Levi', 'Judah', 'Dan',
  'Naphtali', 'Gad', 'Asher', 'Issachar', 'Zebulun', 'Benjamin',
  'Joseph', 'Ephraim', 'Manasse']
>>> ht = Hashtable(21)
>>> for name in tribes:
       ht.insert(name)
>>> ht # calls repr___
      (next slide)
```

## Example: A slightly larger table (n = 14, m = 21)

```
>>> ht # calls repr
0 []
1 []
2 []
3 ['Ephraim']
4 []
5 ['Issachar']
6 ['Benjamin']
7 []
8 ['Judah']
9 ['Naphtali']
10 []
11 []
12 ['Zebulun']
13 ['Manasse']
14 []
15 ['Reuben', 'Dan']
16 []
17 ['Gad']
18 ['Levi']
19 []
20 ['Simeon', 'Asher', 'Joseph']
```

## Hashing and User-defined Classes

 So far, we used our Hashtable class to store Python's built-in (immutable) types such as str, tuple and int.

 But what if we want to use Hashtable with a user-defined class (such as class Student)?

Let's explore this gradually.

## Hashing class Point

Let's start with a simple experiment:

```
class Point:
    def __init__ (self, x, y):
        self.x = x
        self.y = y

>>> p1 = Point(4,7)
    >>> p2 = Point(4,7)
    >>> hash(p1) == hash(p2)

False
    >>> p1 is p2
False
```

- By default, Python uses the memory address of an object to compute the value of hash on it.
- Is this a problem?

## Hashing Python's Types

On the other hand:

```
>>> n1 = 1000
>>> n2 = 1000
>>> hash(n1) == hash(n2)

True
>>> n1 is n2

False
```

```
>>> t1 = (1,2,3)

>>> t2 = (1,2,3)

>>> hash(t1) == hash(t2)

True

>>> t1 is t2

False
```

- Here, Python's hash uses the values of objects, rather than their memory address.
- What do int and tuple (and other hash-able Python types) have that Point doesn't?
- First of all, an implementation for <u>hash</u>, which defines the result of calling Python's hash on an object of this class.

## Adding hash to class Point

• Let's go on with our experiment:

```
class Point:
   def init (self, x, y):
      self.x = x
      self.y = y
                                              calls tuple's
                                              hash__ method
   def hash (self):
      return hash( (self.x, self.y) )
  >>> p1 = Point(4,7)
  >>> p2 = Point(4,7)
  >>> hash(p1) == hash(p2) == hash((4,7))
  True ©
  >>> p1 is p2
  False
```

## Hashing class Point (cont.)

Are we done?

```
>>> p1 = Point(4,7)
>>> p2 = Point(4,7)
>>> hash(p1) == hash(p2) == hash((4,7))
True ©
>>> ht = Hashtable(7)
>>> ht.insert(p1)
>>> p1 in ht
True © not surprising
>>> p2 in ht
False 😂???
```

What are we missing?

```
>>> ht
0 []
1 []
2 []
3 []
4 []
5 [<__main___.Point object at 0x03663D90>]
6 []
```

## Adding eq to class Point

• Let's go on with our experiment:

```
class Point:
   def init (self, x, y):
      self.x = x
      self.y = y
   def hash (self):
      return hash( (self.x, self.y) )
   def eq (self, other):
      return self.x == other.x and self.y == other.y
    >>> p1 = Point(4,7)
                                              calls appropriate
    >>> p2 = Point(4,7)
                                                eq method
    >>> ht = Hashtable(7)
    >>> ht.insert(p1)
    >>> p2 in ht
    True © finally...
```

#### Hashing User Defined Classes: Summary

- Indeed, there is not much point in having \_\_hash\_\_ without \_\_eq\_\_.
- The former directs us to the appropriate chain
- The latter is needed to compare the searched object to elements within that chain.

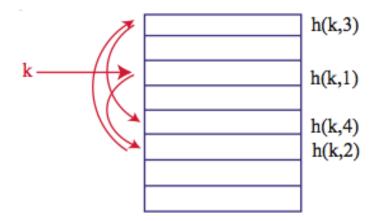
- Note: user-defined classes in Python are by default mutable.
- By implementing \_\_hash\_\_ you are "making a promise" that your class will avoid any mutations (there are ways to make this more than just a promise, but it's out of the scope in our course).

## Dealing with Collision – Open Addressing (for reference only)

 In open addressing, each slot in the hash table contains at most one item. This obviously implies that n cannot be larger than m.

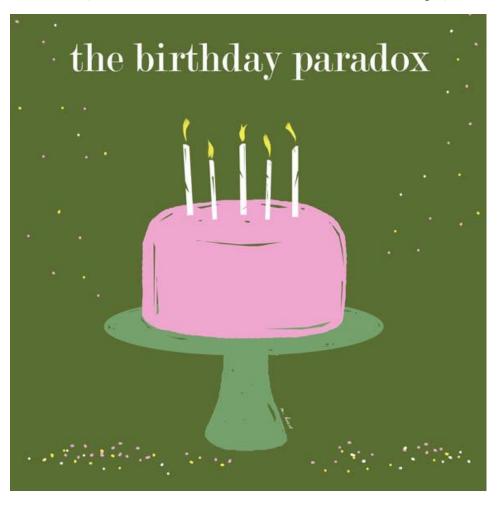
Each element enters the first vacant cell among a series of hash

outputs:



- Open addressing is important in hardware applications where devices have many slots, but each can only store one item (e.g., fast switches and high-capacity routers). It is also used in python dictionaries and sets.
- There are many approaches to open addressing. A fairly recent one is
   termed cuckoo hashing (Pagh and Rodler, 2001).

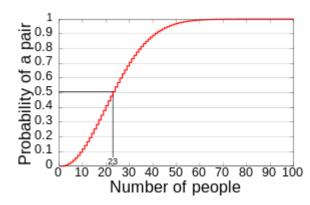
# A Related Issue: The Birthday Paradox (for reference only)



(figure taken from http://thenullhypodermic.blogspot.co.il/2012\_03\_01\_archive.html)

# The Birthday Paradox (for reference only)

- A well known (and not too hard to prove) result is that if we throw n balls at random into m distinct slots, and  $n \approx \sqrt{\pi \cdot m/2}$  then with probability about 0.5, two balls will end up in the same slot.
- For m = 365 we get  $\sqrt{\pi \cdot 365/2} \approx 23.94$



From Wikipedia: The computed probability of at least two people sharing a birthday versus the number of people

- This gives rise to the so called "birthday paradox" given 24 people with random birth dates (month and day of month), with probability > 0.5 two will have the same birth date
- Thus, if our set of keys is of size  $n > \sqrt{\pi \cdot m/2}$  most likely there will be a collision