Randomized Data Structures: Hash Tables

Admin

- Assignment 8 is tonight
- Assignment 9 will be released today
 - Last assignment to be turned in
- Health day: no Lecture on Friday



- Final will be open book, take home 24-hour exam
 - Can be taken between May 20 until May 28 (by 8.30 pm)
 - Logistics will be similar to the midterm

- Array of size m that can store up to n items
 - Often have m = 2n or m = 1.5n

- Want O(1) expected operations:
 - Insert a new item
 - Look up an item
 - Delete an item (we won't discuss)

• Key: hash function that maps each item to a slot

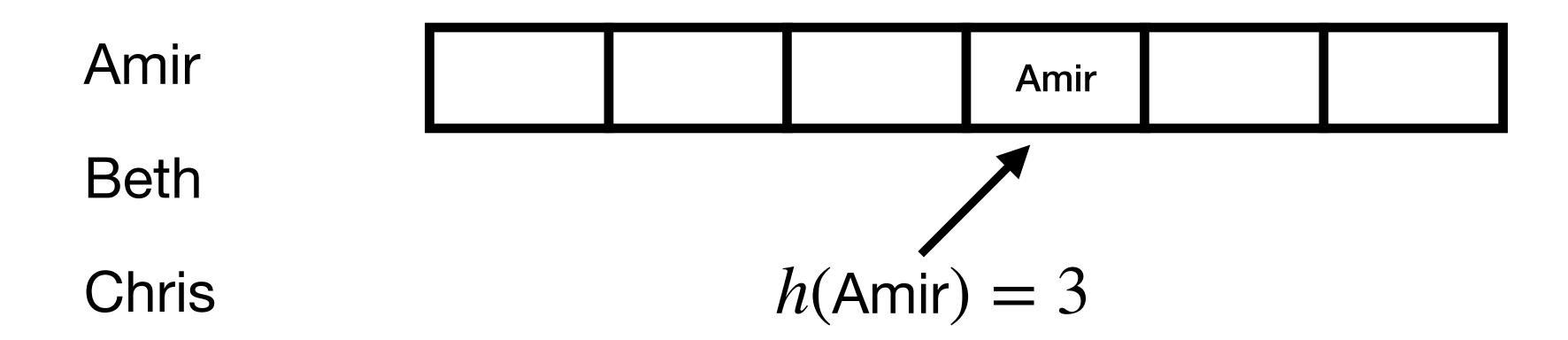
- Hash function h, array A
- Item i is stored in A[h(i)]
- Let's assume that there is only one item that hashes to each slot. Then, we're done: O(1) time insert, lookup, delete

Amir

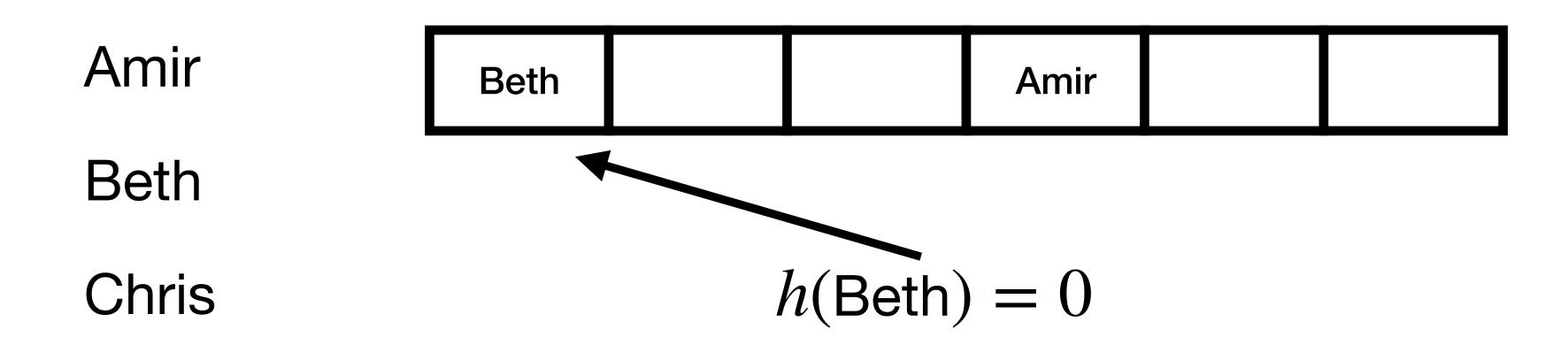
Beth

Chris

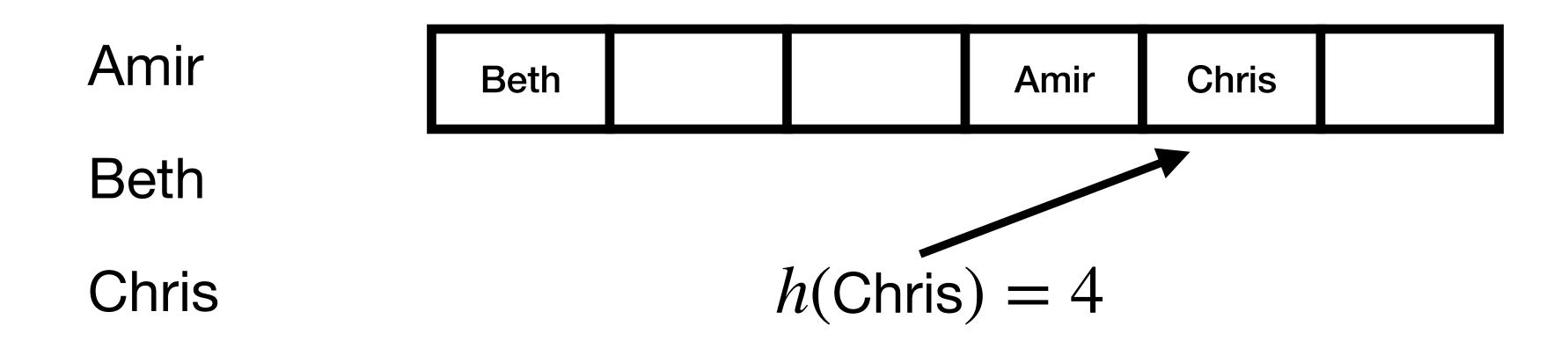
- Hash function h, array A
- Item i is stored in A[h(i)]
- Let's assume that there is only one item that hashes to each slot. Then, we're done: O(1) time insert, lookup, delete



- Hash function h, array A
- Item i is stored in A[h(i)]
- Let's assume that there is only one item that hashes to each slot. Then, we're done: O(1) time insert, lookup, delete



- Hash function h, array A
- Item i is stored in A[h(i)]
- Let's assume that there is only one item that hashes to each slot. Then, we're done: O(1) time insert, lookup, delete



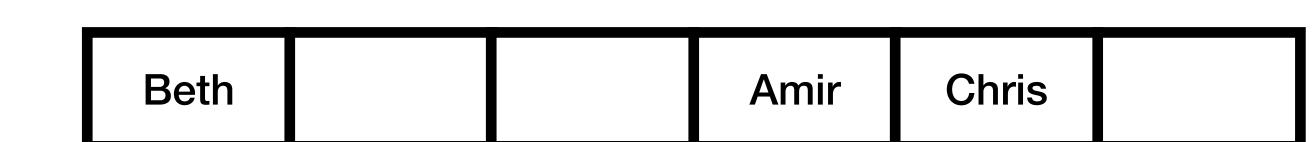
Hash function

- Goal: for any set of items, the hash function maps the items to different slots as much as possible (spreads them out)
- How can we achieve this?
- Idea: use randomness



Hash function: theory versus practice

- Select a hash function from a random family
- Classic example:
- $h(i) = (ai + b) \mod p \mod m$

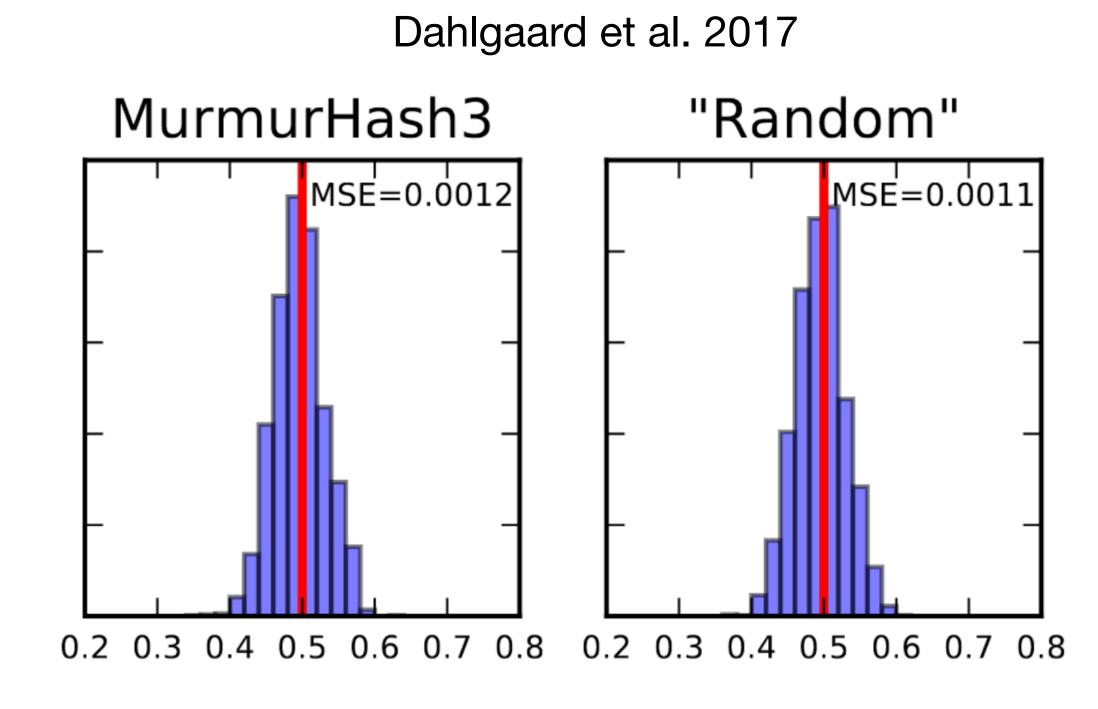


- a and b are chosen at random; selecting them determines the exact hash function
- p is a large prime
- For any items i_1, i_2 : $\Pr_{a,b} \left[h(i_1) = h(i_2) \right] = 1/m$
- By choosing a *random* hash function, we can guarantee that *any* two items probably don't collide

Hash function: theory versus practice

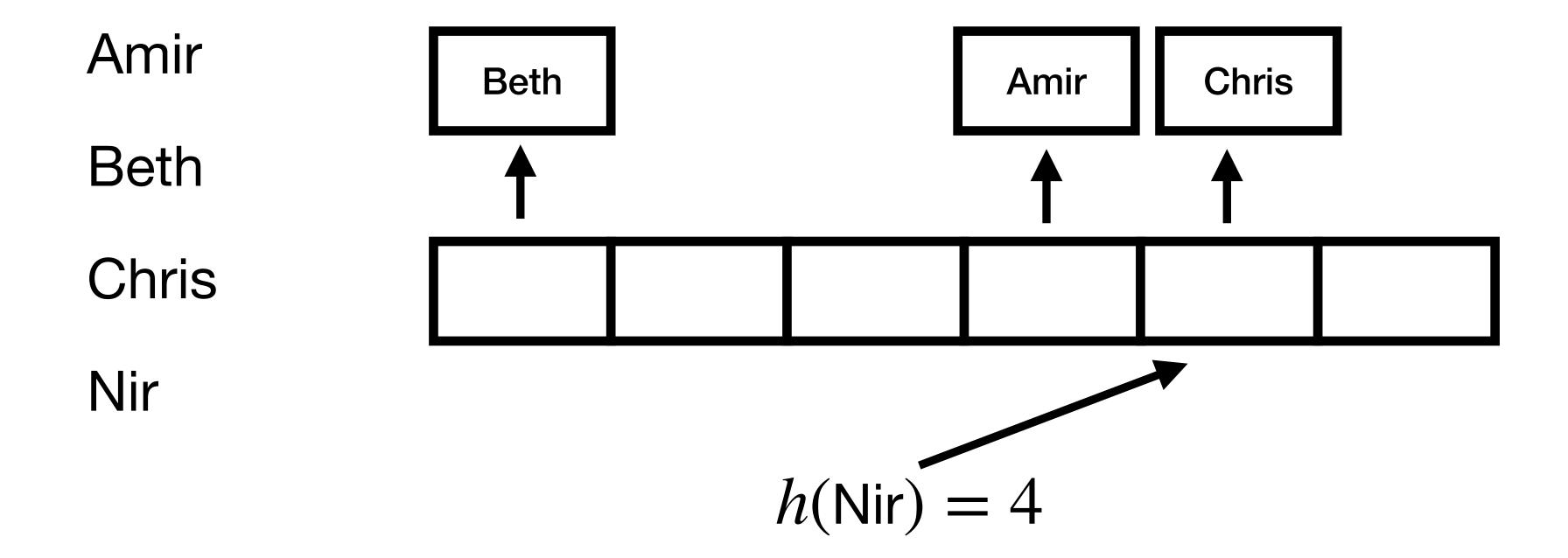
- We will assume hash function is ideal:
 - For all i, k, Pr(h(i) = k) = 1/m
 - The hashes of all items are independent: $\Pr(h(i) = k \mid h(i_2) = k_2, h(i_3) = k_3, ...) = 1/m$

- Called uniform random hash functions
- Good hash functions do behave this way in practice
- Lots of theoretical work about weaker assumptions on the hash functions



Chaining

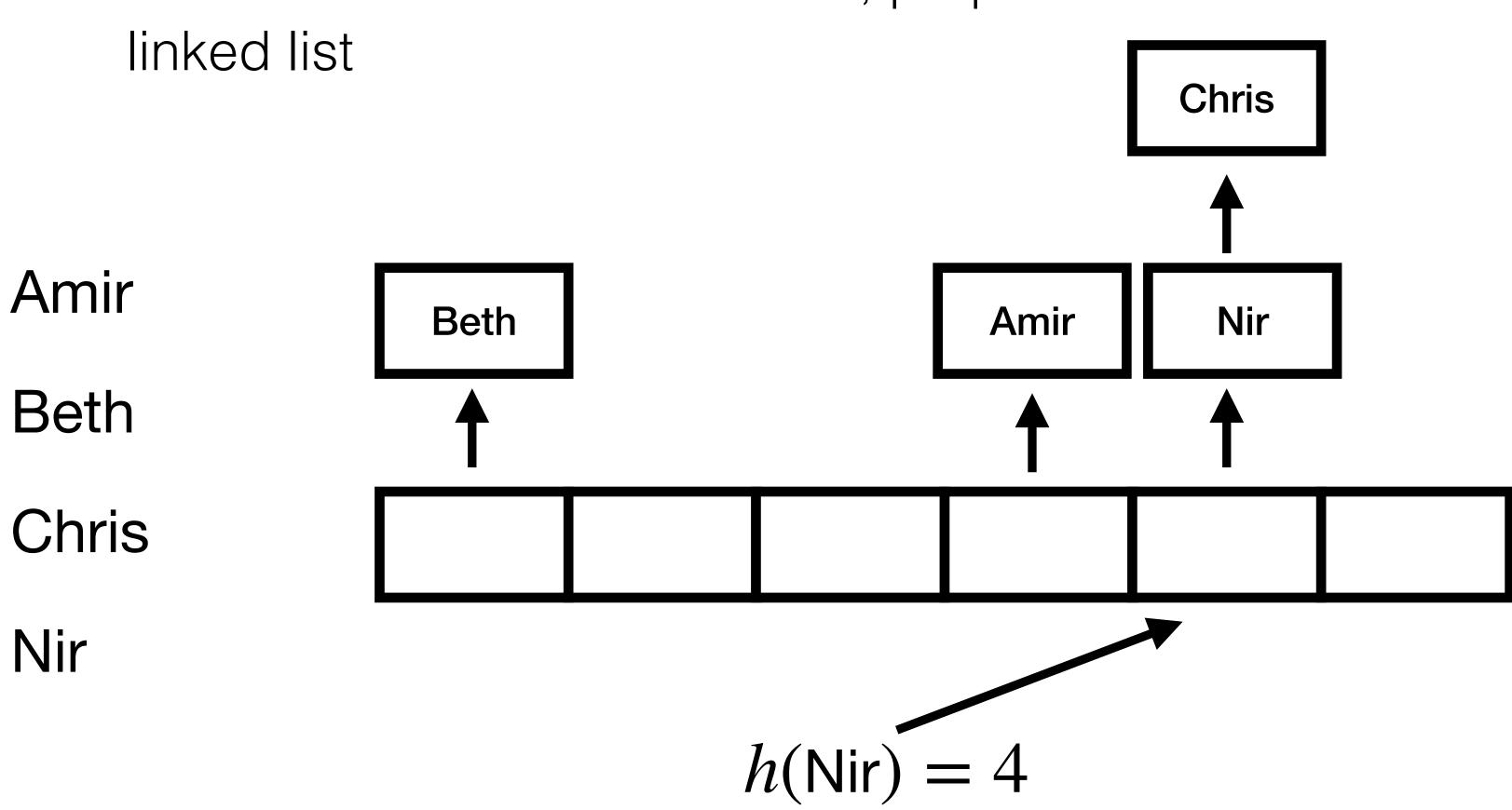
- Store a linked list at each array entry
- When an item hashes to a slot, prepend it to the linked list



Chaining

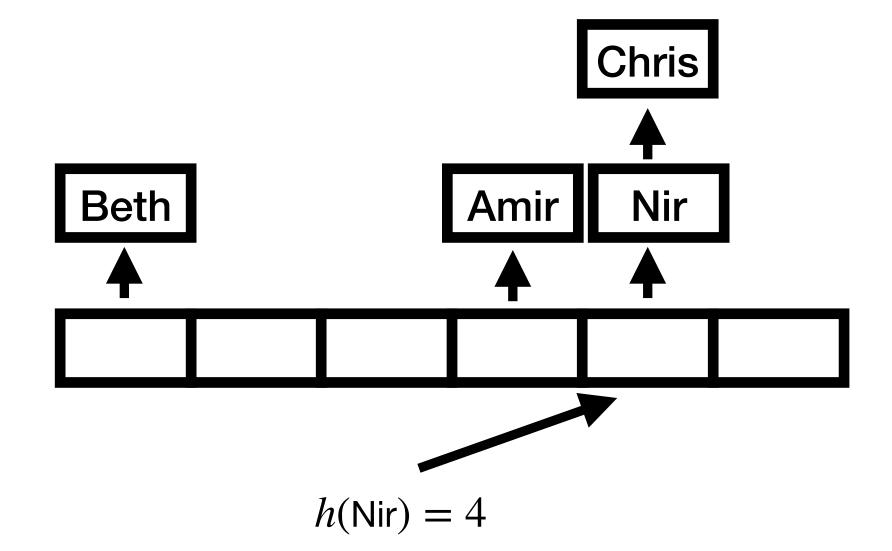
Store a linked list at each array entry

When an item hashes to a slot, prepend it to the



Chaining

- Store a linked list at each array entry
- When an item hashes to a slot, prepend it to the linked list



How can we insert?

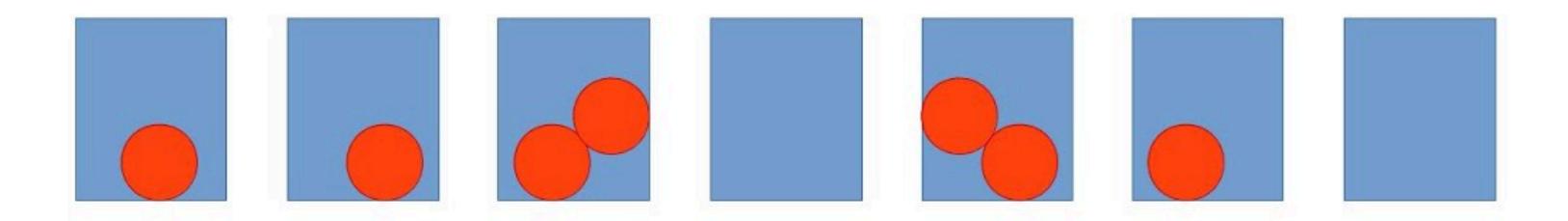
How can we lookup?

How much time does insert/lookup take?

Hash Tables Analysis: via Balls and Bins

Balls and Bins

- Consider the process of throwing n balls into m bins
- Each ball is thrown into a uniformly random bin, independent of other balls
- What does the distribution of balls in bins looks like?
- This process helps analyze hashing, other processes
 - Distributed load balancing (assigning requests to servers), etc.



Balls and Bins: Hashing

- Expected lookup time in a hash table with chaining
 - Same as expected number of balls in a particular bin
- Question. Expected number of balls in a particular bin b?
- Homework 8, Problem 2
- As long as table size m is constant factor of number of elements n, expected cost of hashing with chaining is O(1)
- Expectation is just average; but how long can the chains get?
 - How many balls in the fullest bin?
 - Turns out, not too big even if m = n

- **Lemma.** If n balls are thrown independently and uniformly into n bins, then with high probability, the fullest bin contains $O\left(\frac{\log n}{\log \log n}\right)$
- To prove this we first answer a few helpful questions
- What is the probability that a bin has exactly k balls?

$$\cdot \binom{n}{k} \left(\frac{1}{n}\right)^k \left(1 - \frac{1}{n}\right)^{n-k}$$

• Let X be the number of balls in a bin, then X has a **binomial distribution**

- **Lemma.** If n balls are thrown independently and uniformly into n bins, then with high probability, the fullest bin contains $O\left(\frac{\log n}{\log \log n}\right)$
- To prove this we first answer a few helpful questions
- What is the probability that a bin has exactly k balls?

$$\cdot \binom{n}{k} \left(\frac{1}{n}\right)^k \left(1 - \frac{1}{n}\right)^{n-k}$$

• Let X be the number of balls in a bin, then X has a **binomial distribution**

- **Lemma.** If n balls are thrown independently and uniformly into n bins, then with high probability, the fullest bin contains $O(\frac{\log n}{\log \log n})$
- The probability that a bin has at least k balls? $\leq \binom{n}{k} \left(\frac{1}{n}\right)^k$
- Select k balls, and multiply with probability they land in the bin, the other n-k balls can land anywhere

- **Lemma.** If n balls are thrown independently and uniformly into n bins, then with high probability, the fullest bin contains $O(\frac{\log n}{\log \log n})$
- The probability that a bin has at least k balls? $\leq \binom{n}{k} \left(\frac{1}{n}\right)^k$ $\leq \left(\frac{en}{k}\right)^k \frac{1}{n^k} = \left(\frac{e}{k}\right)^k$
- Recall death-bed formula $\left(\frac{y}{x}\right)^x \le \left(\frac{y}{x}\right) \le \left(\frac{ey}{x}\right)^x$
- $\text{Let } k = \frac{4 \ln n}{\ln \ln n}$

- **Lemma.** If n balls are thrown independently and uniformly into n bins, then with high probability, the fullest bin contains $O(\frac{\log n}{\log \log n})$
- Probability that a bin has at least $\frac{4 \ln}{\ln \ln n}$ balls

$$\leq \left(\frac{e}{k}\right)^k = \left(\frac{e \ln \ln n}{4 \ln n}\right)^{\frac{4 \ln n}{\ln \ln n}} \leq \left(\frac{e \ln \ln n}{\ln n}\right)^{\frac{4 \ln n}{\ln \ln n}} = e^{\frac{4 \ln n}{\ln \ln n} \cdot \ln \frac{\ln \ln n}{\ln n}}$$

$$= e^{\frac{4 \ln n}{\ln \ln n} \cdot \left(\ln \ln \ln n - \ln \ln n \right)}$$

$$= e^{-4\ln n + \frac{4\ln n \ln \ln \ln n}{\ln \ln n}} \le e^{-3\ln n} = \frac{1}{n^3} \text{ for sufficiently large } n$$

• Thus, $\Pr[bin b \text{ has at least } 4 \ln n / (\ln \ln n) \text{ balls}] \leq 1/n^3$

Useful: Union Bound

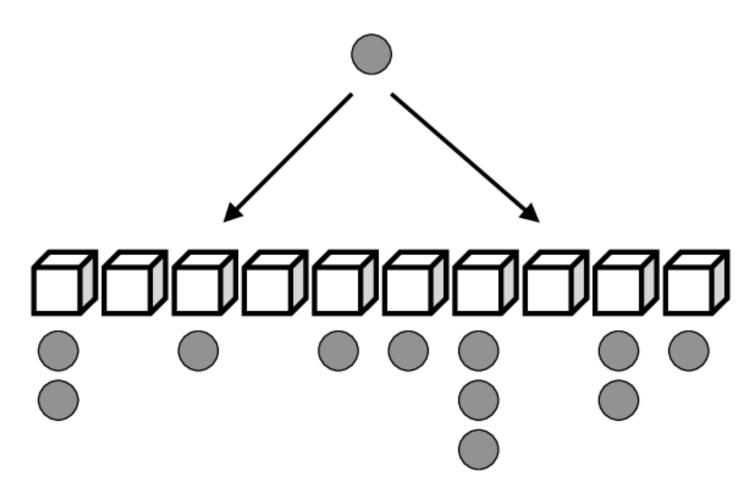
- What we have:
 - $\Pr[bin b \text{ has at least } 4 \ln n / (\ln \ln n) \text{ balls}] \le 1/n^3$
- We want to show that the probability that $any \ bin$ has at least k balls is polynomially small in n
- Useful technique for this
- Union Bound: For any events $A_1, A_2, ..., A_k$, we have

$$\Pr(A_1 \cup A_2 \cup ... \cup A_k) \le \Pr(A_1) + \Pr(A_2) + ... + \Pr(A_k)$$

- **Lemma.** If n balls are thrown independently and uniformly into n bins, then with high probability, the fullest bin contains $O(\frac{\log n}{\log \log n})$
- By union bound, the probability that any bin has at least $k = 4 \frac{\ln n}{\ln \ln n}$ balls is $\sum_{k=1}^n \Pr[\text{bin } b \text{ has at least } 4 \ln n/(\ln \ln n) \text{ balls}] \le \sum_{k=1}^n \frac{1}{n^3} = \frac{1}{n^2}$
- Thus, with high probability the fullest bin contains $O(\frac{\log n}{\log \log n})$ balls
- **Note.** This bound is tight: fullest bins contains $\Theta(\frac{\log n}{\log \log n})$ balls w.h.p.

Aside: Power of Two Choices

- If we thrown n balls into n bins independently and uniformly at random then the max load is $\Theta\left(\frac{\log n}{\log\log n}\right)$
- Fun fact. For each balls, if we instead pick two bins independently and uniformly at random, and put the ball in the less loaded bin, then the max load is at most $\frac{\log \log n}{\log 2} + O(1)$
- Exponential improvement
- ullet Can be generalized to any d choices



Aside: Balls and Bins

- Question. How large must *n* be that it is likely there is a bin with at least two balls?
- Probability that all n balls fall into different bins
- Have we studied this question?
 - Birthday paradox!

Aside: Balls and Bins

- Question. How many balls *n* should be thrown until all bins have at least one ball?
- Pr[bin b is empty] = $\left(1 \frac{1}{n}\right)^m \approx e^{-m/n}$

 $\left(\left(1 - \frac{1}{x}\right)^x \le \frac{1}{e}$

• Pr[exists an empty bin] = Pr[$\bigcup_{b=1}^{m}$ bin b is empty]

$$\leq \sum_{b=1}^{m} \Pr[\text{bin } b \text{ is empty}] = m \cdot e^{-n/m}$$

- E.g. $n = 3m \ln m$, the probability is at most $\frac{1}{m^2}$
- That is, if we buy $\Theta(m \log m)$ packs, we get all Pokemons w.h.p.

Back to Hashing

Hashing with Chaining

- Let's say I store the first element of the chain in the table itself
- Then I don't need a linked list for chains of length 1
- How many chains of length 1 will I have in expectation?
- We'll assume n = m
- Let's analyze this using indicator random variables
- Random variable $X_i = 1$ if slot i has exactly one item, 0 otherwise
- By linearity of expectation, we want $\sum_{i=1}^{n} \Pr[\text{slot } i \text{ has one item}]$

Chaining: Some other questions

• Pr [slot *i* has one item]

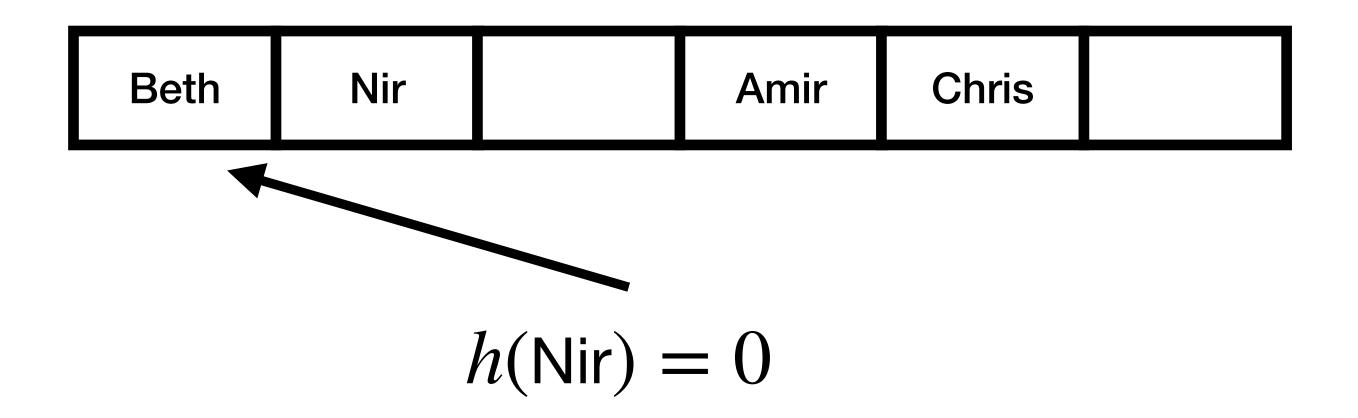
$$= \binom{n}{1} \left(\frac{1}{n}\right) \left(1 - \frac{1}{n}\right)^{n-1}$$

$$= \left(1 - \frac{1}{n}\right)^{n-1} \le \left(1 - \frac{1}{n}\right)^n \le \frac{1}{e}$$

• So expected number of slots with a chain of length 1 is n/e

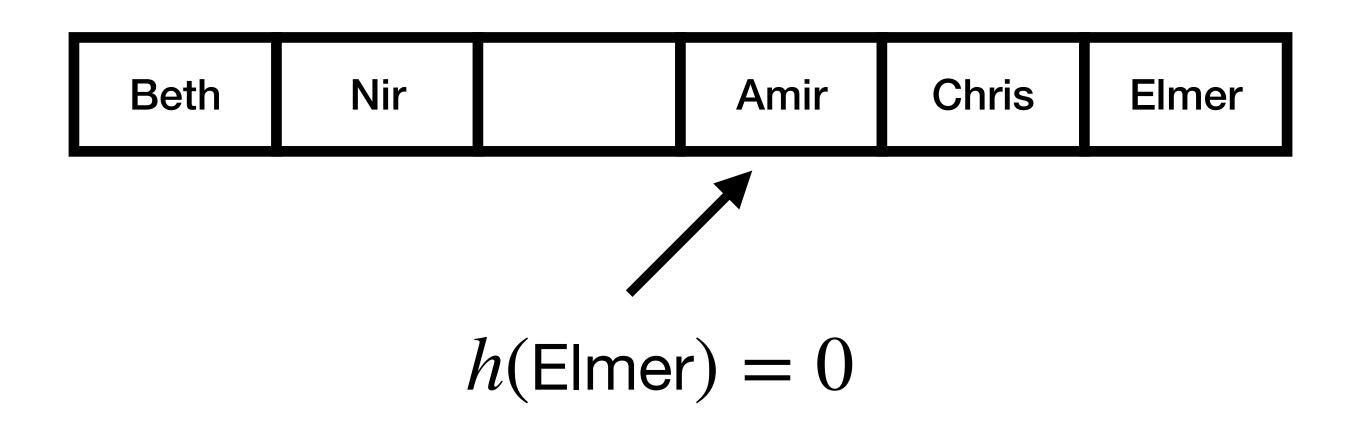
Linear Probing

- No linked lists; just the table
- If there is already an item in A[h(i)], check A[h(i)+1], then A[i+2], and so on

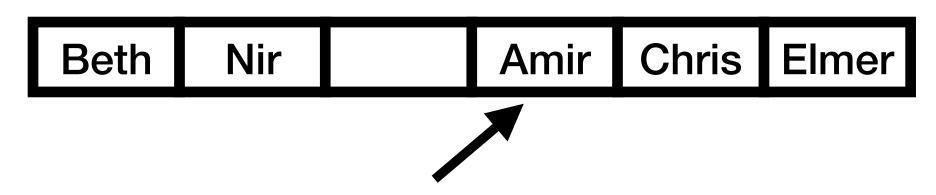


Linear Probing

- No linked lists; just the table
- If there is already an item in A[h(i)], check A[h(i)+1], then A[i+2], and so on
- How can we insert?
- How can we lookup?
- How much time does insert/lookup take?



Linear Probing



- Calculations are a bit harder because inserts depend on each other
- h(Elmer) = 0

- Larger clusters are more likely to be hashed to, so their size grows
- Expected lookup time if successful [Knuth]:
- O(1 + 1/(1 n/m))
- Expected insert/unsuccessful lookup:
- $O(1 + 1/(1 n/m)^2)$
- Can show all operations are $O(\log n)$ w.h.p. using similar techniques

Linear Probing vs Chaining?

- What are some advantages of chaining?
 - Constant time inserts
 - Better w.h.p. performance
- What are some advantages of linear probing?
 - Space-efficient
 - Better cache efficiency
- Linear probing is the more common one in practice

Improving Worst Case Lookups

We need randomness in order to hash

But can we get worst-case bounds?

• For example, can we get O(1) worst-case lookup, with O(1) expected insert (and $O(\log n)$ insert with high probability)?

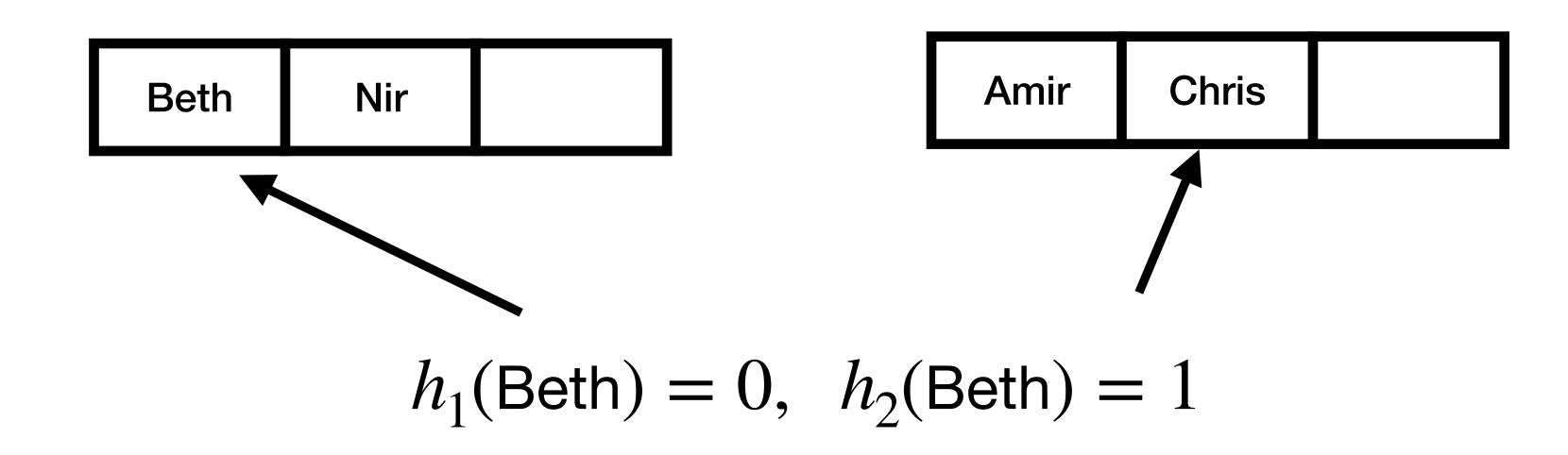
Yes—cuckoo hashing!

Cuckoo Hashing

Cuckoo Hashing

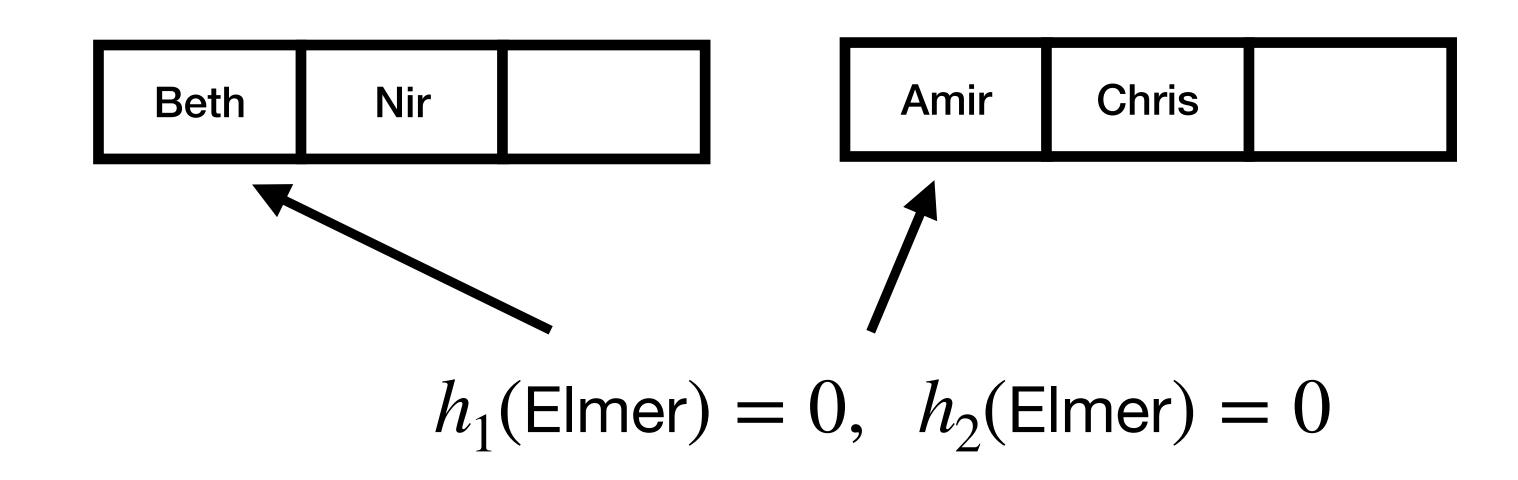
- Uses two hash functions, h_1 and h_2 , two hash tables
- Each table size *n*
- Item i is guaranteed to be in $A[h_1(i)]$ or $A[h_2(i)]$
- So we can lookup in O(1)
- How can we insert?





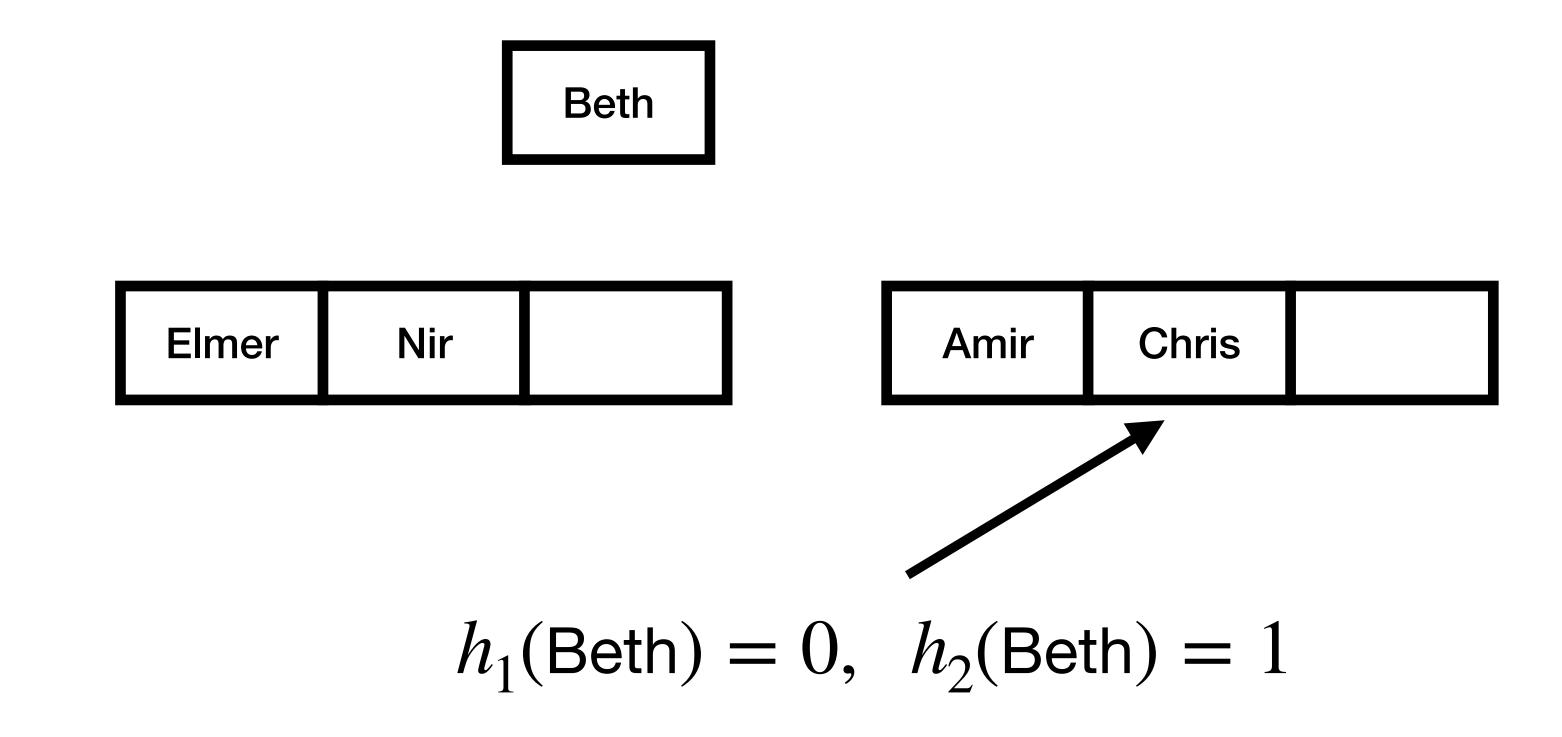
- If $A[h_1(i)]$ or $A[h_2(i)]$ is empty, store i
- Otherwise, kick an item out of one of these locations
- Reinsert that item using its other hash





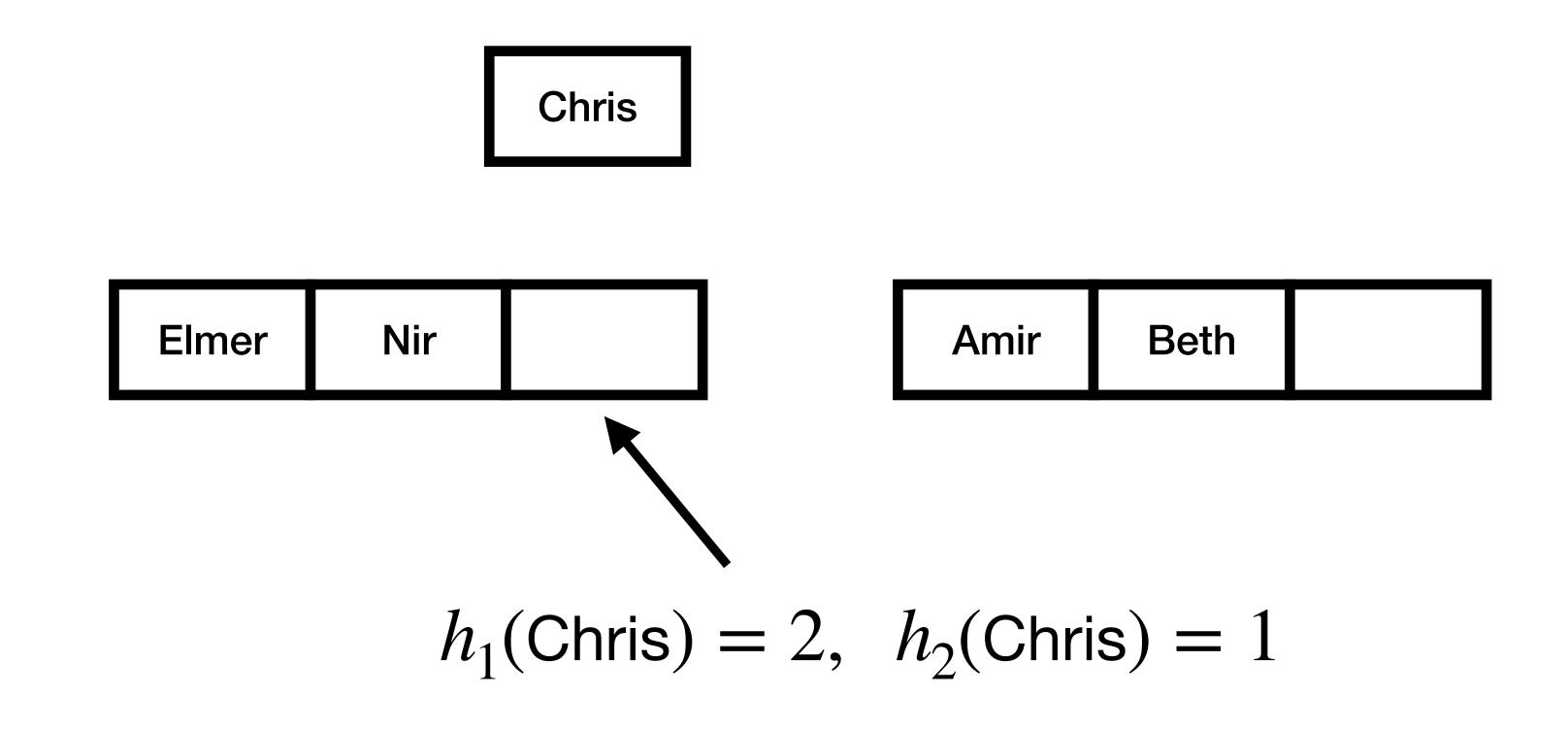
- If $A[h_1(i)]$ or $A[h_2(i)]$ is empty, store i
- Otherwise, kick an item out of one of these locations
- Reinsert that item using its other hash





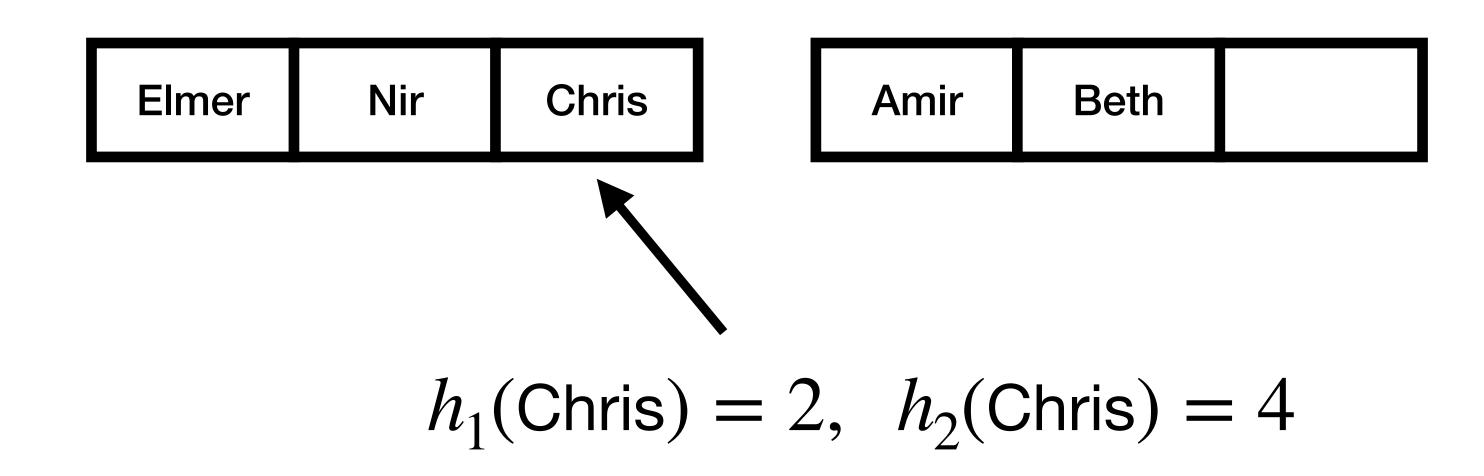
- If $A[h_1(i)]$ or $A[h_2(i)]$ is empty, store i
- Otherwise, kick an item out of one of these locations
- Reinsert that item using its other hash



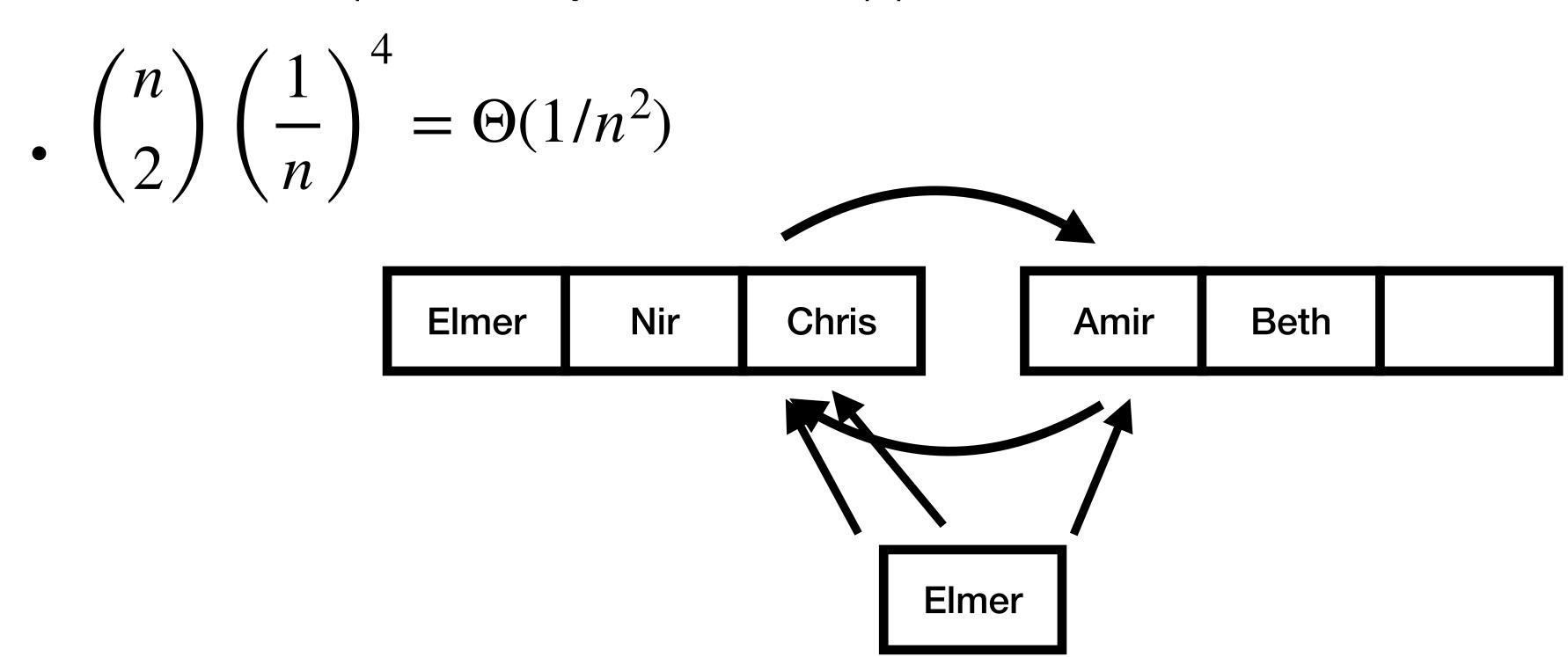


- If $A[h_1(i)]$ or $A[h_2(i)]$ is empty, store i
- Otherwise, kick an item out of one of these locations
- Reinsert that item using its other hash



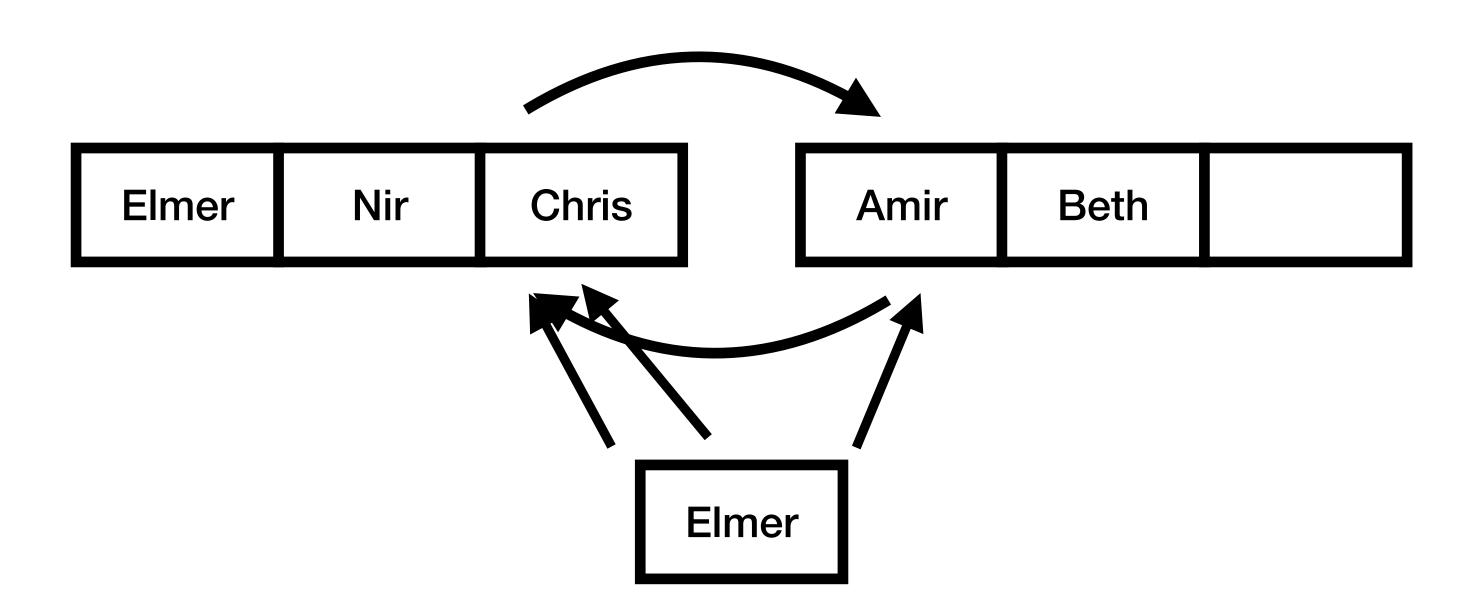


- What can go wrong?
- This process may not end
- Example: 3 items hash to the same two slots
- What is the probability that this happens?





- More complicated analysis:
- Cuckoo hashing fails with probability $O(1/n^2)$
- What happens when we fail?
- Rebuild the whole hash table
- (Expensive worst-case insert operation)





- How long does an insert take on average?
- One idea: each time we go to the other table, what is the probability the slot is empty?
- 1/2. (This analysis isn't 100% right due to some subtle dependencies, but it's the right idea)
- So need two moves to find an empty slot in expectation
- At most $O(\log n)$ with high probability



Next class: Approximation Algorithms

Acknowledgments

- Some of the material in these slides are taken from
 - Kleinberg Tardos Slides by Kevin Wayne (https://www.cs.princeton.edu/~wayne/kleinberg-tardos/pdf/04GreedyAlgorithmsl.pdf)
 - Jeff Erickson's Algorithms Book (http://jeffe.cs.illinois.edu/teaching/algorithms/book/Algorithms-JeffE.pdf)