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So far we have implemented the search for a key by carefully choosing split-elements.

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#### **Definitions:**

- ▶ Universe U of keys, e.g.,  $U \subseteq \mathbb{N}_0$ . U very large.
- ▶ Set  $S \subseteq U$  of keys,  $|S| = m \le |U|$ .
- Array T[0, ..., n-1] hash-table
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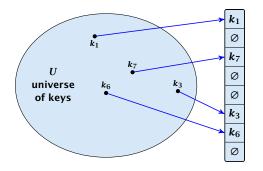
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# **Direct Addressing**

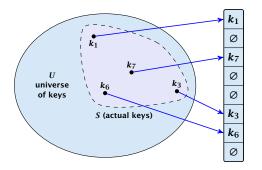
Ideally the hash function maps all keys to different memory locations.



This special case is known as Direct Addressing. It is usually very unrealistic as the universe of keys typically is quite large, and in particular larger than the available memory.

# **Perfect Hashing**

Suppose that we know the set S of actual keys (no insert/no delete). Then we may want to design a simple hash-function that maps all these keys to different memory locations.



Such a hash function h is called a perfect hash function for set S.

If we do not know the keys in advance, the best we can hope for is that the hash function distributes keys evenly across the table.

**Problem: Collisions** 

Usually the universe U is much larger than the table-size  $n.\,$ 

Hence, there may be two elements  $k_1, k_2$  from the set S that map to the same memory location (i.e.,  $h(k_1) = h(k_2)$ ). This is called a collision.

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Typically, collisions do not appear once the size of the set S of actual keys gets close to n, but already when  $|S| \ge \omega(\sqrt{n})$ .

#### Lemma

The probability of having a collision when hashing m elements into a table of size n under uniform hashing is at least

$$1 - e^{-\frac{m(m-1)}{2n}} \approx 1 - e^{-\frac{m^2}{2n}} .$$

## **Uniform hashing:**

Choose a hash function uniformly at random from all functions  $f: U \to [0, \dots, n-1]$ .

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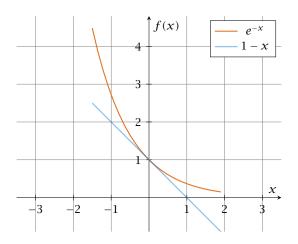
#### Proof.

Let  $A_{m,n}$  denote the event that inserting m keys into a table of size n does not generate a collision. Then

$$\Pr[A_{m,n}] = \prod_{\ell=1}^{m} \frac{n-\ell+1}{n} = \prod_{j=0}^{m-1} \left(1 - \frac{j}{n}\right)$$

$$\leq \prod_{j=0}^{m-1} e^{-j/n} = e^{-\sum_{j=0}^{m-1} \frac{j}{n}} = e^{-\frac{m(m-1)}{2n}}.$$

Here the first equality follows since the  $\ell$ -th element that is hashed has a probability of  $\frac{n-\ell+1}{n}$  to not generate a collision under the condition that the previous elements did not induce collisions.



The inequality  $1-x \le e^{-x}$  is derived by stopping the Taylor-expansion of  $e^{-x}$  after the second term.

# **Resolving Collisions**

The methods for dealing with collisions can be classified into the two main types

- open addressing, aka. closed hashing
- hashing with chaining, aka. closed addressing, open hashing.

There are applications e.g. computer chess where you do not resolve collisions at all.

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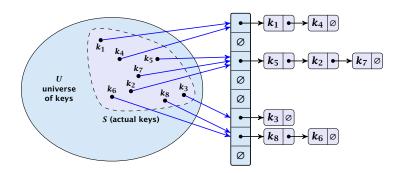
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There are applications e.g. computer chess where you do not resolve collisions at all.

Arrange elements that map to the same position in a linear list.

- Access: compute h(x) and search list for key[x].
- Insert: insert at the front of the list.



# Let A denote a strategy for resolving collisions. We use the following notation:

- ▶  $A^+$  denotes the average time for a **successful** search when using A;
- A<sup>-</sup> denotes the average time for an unsuccessful search when using A;
- We parameterize the complexity results in terms of  $\alpha := \frac{m}{n}$ , the so-called fill factor of the hash-table.

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7.7 Hashing

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$$A^- = 1 + \alpha .$$

For a successful search observe that we do **not** choose a list at random, but we consider a random key k in the hash-table and ask for the search-time for k.

This is 1 plus the number of elements that lie before *k* in *k*'s list.

Let  $k_{\ell}$  denote the  $\ell$ -th key inserted into the table.

Let for two keys  $k_i$  and  $k_j$ ,  $X_{ij}$  denote the indicator variable for the event that  $k_i$  and  $k_j$  hash to the same position. Clearly,  $\Pr[X_{ij}=1]=1/n$  for uniform hashing.

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The expected successful search cost is

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Hence, the expected cost for a successful search is  $A^+ \leq 1 + \frac{\alpha}{2}$ .

#### Disadvantages:

- pointers increase memory requirements
- pointers may lead to bad cache efficiency

#### **Advantages:**

- no à priori limit on the number of elements
- deletion can be implemented efficiently
- by using balanced trees instead of linked list one can also obtain worst-case guarantees.

All objects are stored in the table itself.

Define a function h(k, j) that determines the table-position to be examined in the j-th step. The values  $h(k, 0), \ldots, h(k, n-1)$  must form a permutation of  $0, \ldots, n-1$ .

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#### Choices for h(k, j):

Linear probing:

$$h(k,i) = h(k) + i \mod n$$
  
(sometimes:  $h(k,i) = h(k) + ci \mod n$ ).

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#### Choices for h(k, j):

Linear probing:  $h(k, i) = h(k) + i \mod n$ (sometimes:  $h(k, i) = h(k) + ci \mod n$ ).

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### **Linear Probing**

- Advantage: Cache-efficiency. The new probe position is very likely to be in the cache.
- Disadvantage: Primary clustering. Long sequences of occupied table-positions get longer as they have a larger probability to be hit. Furthermore, they can merge forming larger sequences.

#### Lemma 2

Let  ${f L}$  be the method of linear probing for resolving collisions:

$$L^{+} \approx \frac{1}{2} \left( 1 + \frac{1}{1 - \alpha} \right)$$
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Any probe into the hash-table usually creates a cache-miss.

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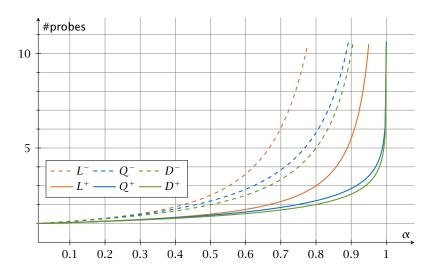
$$D^- \approx \frac{1}{1-\alpha}$$

#### **Open Addressing**

#### Some values:

α	Linear Probing		Quadratic Probing		Double Hashing	
	$L^+$	$L^{-}$	$Q^+$	$Q^-$	$D^+$	$D^-$
0.5	1.5	2.5	1.44	2.19	1.39	2
0.9	5.5	50.5	2.85	11.40	2.55	10
0.95	10.5	200.5	3.52	22.05	3.15	20

#### **Open Addressing**





We analyze the time for a search in a very idealized Open Addressing scheme.

► The probe sequence h(k,0), h(k,1), h(k,2),... is equally likely to be any permutation of (0,1,...,n-1).

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$$\le \left(\frac{m}{n}\right)^{i-1} = \alpha^{i-1} .$$

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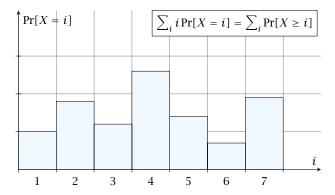
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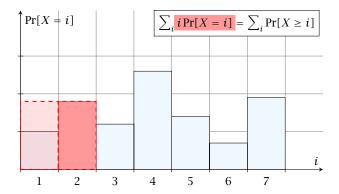
$$\frac{1}{1-\alpha}=1+\alpha+\alpha^2+\alpha^3+\dots$$



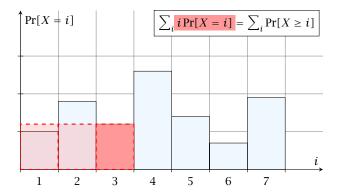
i = 1



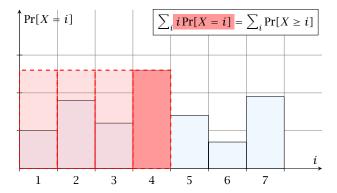
$$i = 2$$



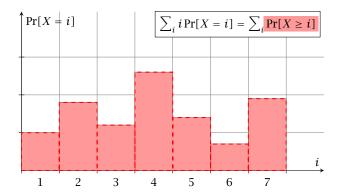
$$i = 3$$



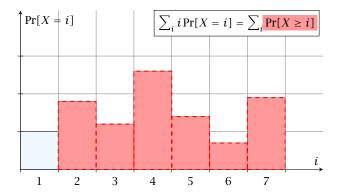
i = 4



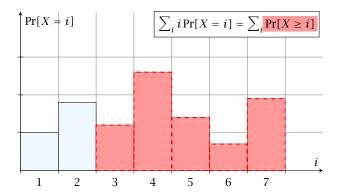
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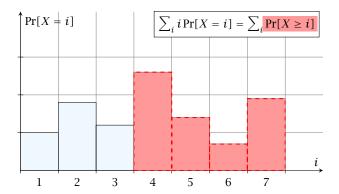
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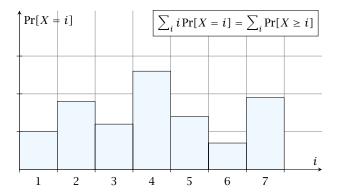


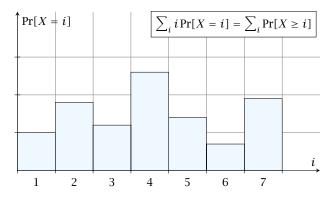
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The j-th rectangle appears in both sums j times. (j times in the first due to multiplication with j; and j times in the second for summands i = 1, 2, ..., j)

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# **Analysis of Idealized Open Address Hashing**

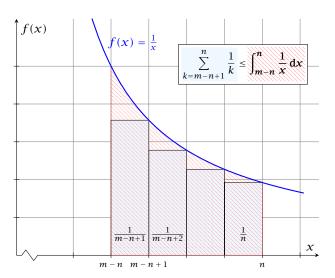
The number of probes in a successful search for k is equal to the number of probes made in an unsuccessful search for k at the time that k is inserted.

Let k be the i+1-st element. The expected time for a search for k is at most  $\frac{1}{1-i/n}=\frac{n}{n-i}$ .

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- One can delete an element by replacing it with a deleted-marker.

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7.7 Hashing

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Therefore, so far we assumed that the hash-function is random so that regardless of the input the average case behaviour is good.

However, the assumption of uniform hashing that h is chosen randomly from all functions  $f:U\to [0,\ldots,n-1]$  is clearly unrealistic as there are  $n^{|U|}$  such functions. Even writing dowr such a function would take  $|U|\log n$  bits.

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#### **Definition 5**

A class  $\mathcal H$  of hash-functions from the universe U into the set  $\{0,\dots,n-1\}$  is called universal if for all  $u_1,u_2\in U$  with  $u_1\neq u_2$ 

$$\Pr[h(u_1) = h(u_2)] \le \frac{1}{n} ,$$

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- For any key  $u \in U$ , and  $t \in \{0, ..., n-1\}$   $\Pr[h(u) = t] = \frac{1}{n}$ , i.e., a key is distributed uniformly within the hash-table.
- For all  $u_1, u_2 \in U$  with  $u_1 \neq u_2$ , and for any two hash-positions  $t_1, t_2$ :

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A class  $\mathcal H$  of hash-functions from the universe U into the set  $\{0,\ldots,n-1\}$  is called k-independent if for any choice of  $\ell \leq k$  distinct keys  $u_1,\ldots,u_\ell \in U$ , and for any set of  $\ell$  not necessarily distinct hash-positions  $t_1,\ldots,t_\ell$ :

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#### **Definition 8**

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$$h_{a,b}(x) := (ax + b \bmod p) \bmod n$$

#### Lemma 9

The class

$$\mathcal{H} = \{ h_{a,b} \mid a \in \mathbb{Z}_p^*, b \in \mathbb{Z}_p \}$$

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$$h_{a,b}(x) := (ax + b \bmod p) \bmod n$$

Lemma 9

The class

$$\mathcal{H} = \{ h_{a,b} \mid a \in \mathbb{Z}_p^*, b \in \mathbb{Z}_p \}$$

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$$a \equiv (t_{x} - t_{y})(x - y)^{-1} \qquad (\text{mod } p)$$

$$b \equiv t_{y} - ay \qquad (\text{mod } p)$$

There is a one-to-one correspondence between hash-functions (pairs (a, b),  $a \neq 0$ ) and pairs  $(t_X, t_Y)$ ,  $t_X \neq t_Y$ .

Therefore, we can view the first step (before the mod noperation) as choosing a pair  $(t_x, t_y)$ ,  $t_x \neq t_y$  uniformly at
random.

What happens when we do the  $\operatorname{mod} n$  operation?

Fix a value  $t_x$ . There are p-1 possible values for choosing  $t_y$ .

From the range  $0, \ldots, p-1$  the values  $t_X, t_X + n, t_X + 2n, \ldots$  map to  $t_X$  after the modulo-operation. These are at most  $\lceil p/n \rceil$  values.

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It is also possible to show that  $\mathcal H$  is an (almost) pairwise independent class of hash-functions.

$$\Pr_{t_{\mathcal{X}} \neq t_{\mathcal{Y}} \in \mathbb{Z}_p^2} \left[ \begin{array}{c} t_{\mathcal{X}} \bmod n = h_1 \\ t_{\mathcal{Y}} \bmod n = h_2 \end{array} \right]$$

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$$\frac{\left\lfloor \frac{p}{n} \right\rfloor^2}{p(p-1)} \le \Pr_{t_X \neq t_Y \in \mathbb{Z}_p^2} \left[ \begin{array}{c} t_X \bmod n = h_1 \\ t_Y \bmod n = h_2 \end{array} \right] \le \frac{\left\lceil \frac{p}{n} \right\rceil^2}{p(p-1)}$$

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Note that the middle is the probability that  $h(x) = h_1$  and  $h(y) = h_2$ . The total number of choices for  $(t_x, t_y)$  is p(p-1). The number of choices for  $t_x$   $(t_y)$  such that  $t_x \mod n = h_1$   $(t_y \mod n = h_2)$  lies between  $\lfloor \frac{p}{n} \rfloor$  and  $\lceil \frac{p}{n} \rceil$ .

#### **Definition 10**

Let  $d \in \mathbb{N}$ ;  $q \ge (d+1)n$  be a prime; and let  $\bar{a} \in \{0,\ldots,q-1\}^{d+1}$ . Define for  $x \in \{0,\ldots,q-1\}$ 

$$h_{\bar{a}}(x) := \left(\sum_{i=0}^d a_i x^i \bmod q\right) \bmod n$$
.

Let  $\mathcal{H}_n^d := \{h_{\bar{a}} \mid \bar{a} \in \{0, \dots, q-1\}^{d+1}\}$ . The class  $\mathcal{H}_n^d$  is (e, d+1)-independent.

Note that in the previous case we had d = 1 and chose  $a_d \neq 0$ .

For the coefficients  $\bar{a} \in \{0, ..., q-1\}^{d+1}$  let  $f_{\bar{a}}$  denote the polynomial

$$f_{\bar{a}}(x) = \Big(\sum_{i=0}^d a_i x^i\Big) \bmod q$$

The polynomial is defined by d + 1 distinct points.

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Fix  $\ell \le d+1$ ; let  $x_1, \ldots, x_\ell \in \{0, \ldots, q-1\}$  be keys, and let  $t_1, \ldots, t_\ell$  denote the corresponding hash-function values.

Let 
$$A^{\ell}=\{h_{\tilde{a}}\in\mathcal{H}\mid h_{\tilde{a}}(x_i)=t_i \text{ for all } i\in\{1,\ldots,\ell\}\}$$
  
Then

$$h_{\bar{a}} \in A^{\ell} \Leftrightarrow h_{\bar{a}} = f_{\bar{a}} \bmod n$$
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$$f_{\bar{a}}(x_i) \in \underbrace{\{t_i + \alpha \cdot n \mid \alpha \in \{0, \dots, \lceil \frac{q}{n} \rceil - 1\}\}}_{=:B_i}$$

In order to obtain the cardinality of  $A^{\ell}$  we choose our polynomial by fixing d+1 points.

We first fix the values for inputs  $x_1,\ldots,x_\ell$ 

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$$\frac{\lceil \frac{q}{n} \rceil^{\ell} \cdot q^{d-\ell+1}}{q^{d+1}} \leq \frac{(\frac{q+n}{n})^{\ell}}{q^{\ell}}$$

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$$\frac{\lceil \frac{q}{n} \rceil^{\ell} \cdot q^{d-\ell+1}}{q^{d+1}} \leq \frac{(\frac{q+n}{n})^{\ell}}{q^{\ell}} \leq \left(\frac{q+n}{q}\right)^{\ell} \cdot \frac{1}{n^{\ell}}$$

# **Universal Hashing**

Therefore the probability of choosing  $h_{\tilde{a}}$  from  $A_{\ell}$  is only

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# **Universal Hashing**

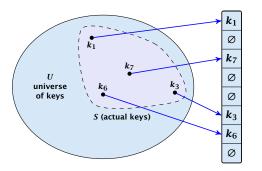
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This shows that the  $\mathcal{H}$  is (e, d+1)-universal.

The last step followed from  $q \ge (d+1)n$ , and  $\ell \le d+1$ .

Suppose that we **know** the set S of actual keys (no insert/no delete). Then we may want to design a **simple** hash-function that maps all these keys to different memory locations.



Let m = |S|. We could simply choose the hash-table size very large so that we don't get any collisions.

Using a universal hash-function the expected number of collisions is

$$E[\#Collisions] = \binom{m}{2} \cdot \frac{1}{n} .$$

If we choose  $n=m^2$  the expected number of collisions is strictly less than  $\frac{1}{2}$ .

Can we get an upper bound on the probability of having collisions?

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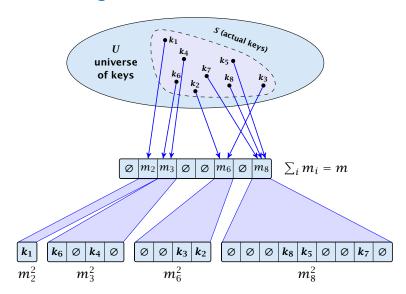
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$$=2\binom{m}{2}\frac{1}{m}+m=2m-1$$
.

We need only  $\mathcal{O}(m)$  time to construct a hash-function h with  $\sum_j m_j^2 = \mathcal{O}(4m)$ , because with probability at least 1/2 a random function from a universal family will have this property.

Then we construct a hash-table  $h_j$  for every bucket. This takes expected time  $\mathcal{O}(m_j)$  for every bucket. A random function  $h_j$  is collision-free with probability at least 1/2. We need  $\mathcal{O}(m_j)$  to test this.

We only need that the hash-functions are chosen from a universal family!!!

#### Goal

```
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```

```
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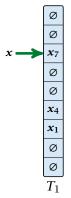
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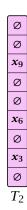
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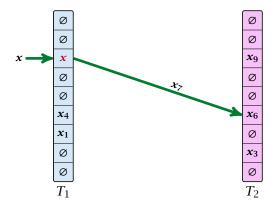
#### Insert:

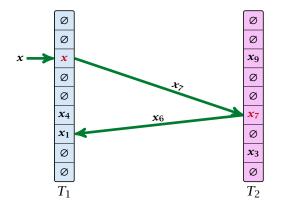


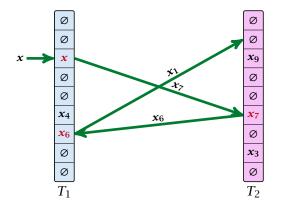
Ø Ø  $x_9$ Ø Ø  $x_6$ Ø  $\boldsymbol{x}_3$ Ø  $T_2$ 











#### **Algorithm 13** Cuckoo-Insert(x)

```
1: if T_1[h_1(x)] = x \lor T_2[h_2(x)] = x then return
2: steps \leftarrow 1
3: while steps \leq maxsteps do
4: exchange x and T_1[h_1(x)]
5: if x = \text{null} then return
6: exchange x and T_2[h_2(x)]
7: if x = \text{null} then return
8: steps \leftarrow steps +1
9: rehash() // change hash-functions; rehash everything
10: Cuckoo-Insert(x)
```

- We call one iteration through the while-loop a step of the algorithm.
- We call a sequence of iterations through the while-loop without the termination condition becoming true a phase of the algorithm.
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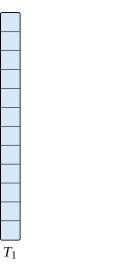
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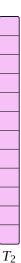
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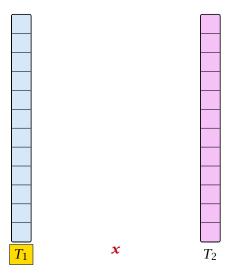
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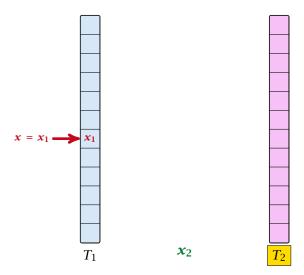
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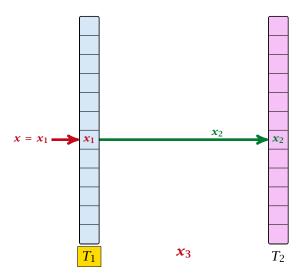
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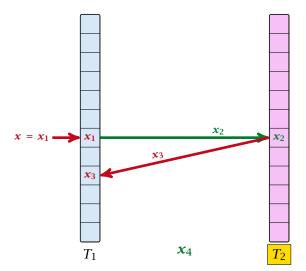


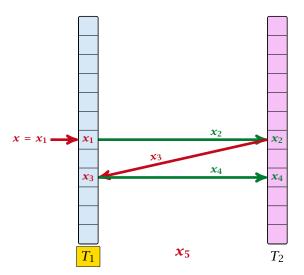


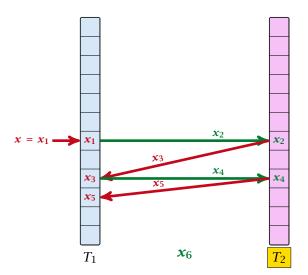


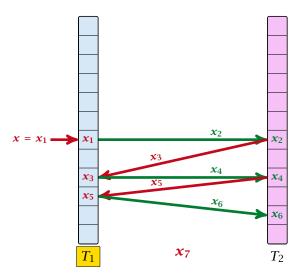


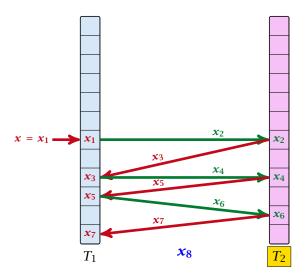


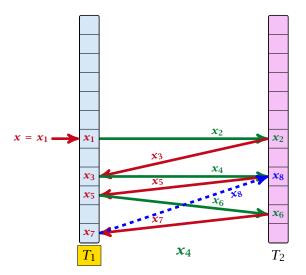


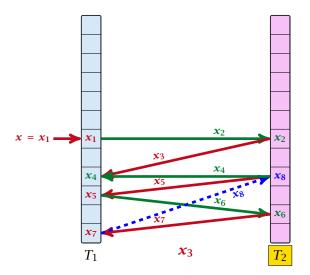


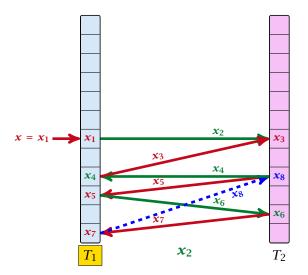


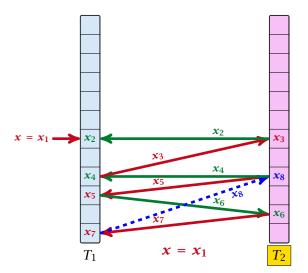


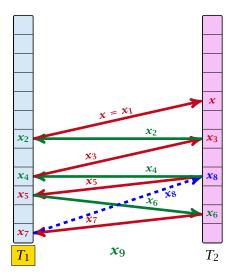


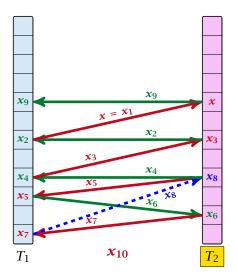


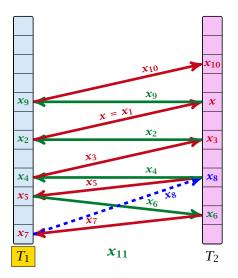


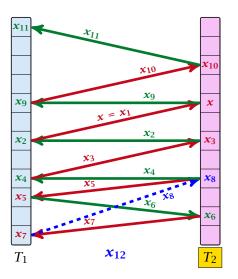


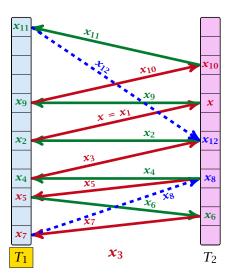


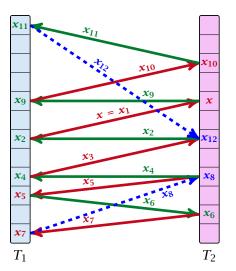


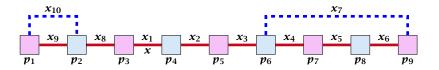


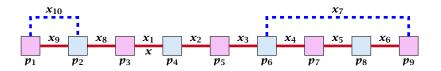




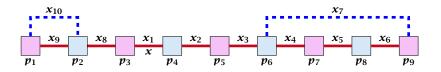




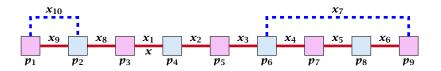




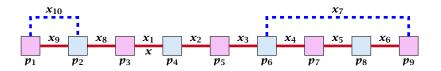
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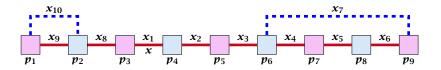
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#### Observation

If during a phase the insert-procedure runs into a cycle there must exist an active cycle structure of size  $s \ge 3$ .

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If during a phase the insert-procedure runs into a cycle there must exist an active cycle structure of size  $s \ge 3$ .

# What is the probability that all keys in a cycle-structure of size s correctly map into their $T_1$ -cell?

This probability is at most  $\frac{\mu}{n^s}$  since  $h_1$  is a  $(\mu, s)$ -independent hash-function.

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This probability is at most  $\frac{\mu}{n^s}$  since  $h_2$  is a  $(\mu, s)$ -independent hash-function.

These events are independent.

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$$\sum_{s=3}^{\infty} s^3 \cdot n^{s-1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}}$$

$$\sum_{s=3}^{\infty} s^3 \cdot n^{s-1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}} = \frac{\mu^2}{nm} \sum_{s=3}^{\infty} s^3 \left(\frac{m}{n}\right)^s$$

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$$\leq \frac{\mu^2}{m^2} \sum_{s=3}^{\infty} s^3 \left(\frac{1}{1+\epsilon}\right)^s$$

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The probability that there exists an active cycle-structure is therefore at most

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Here we used the fact that  $(1 + \epsilon)m \le n$ .

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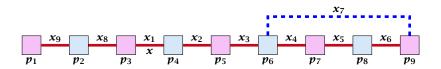
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Hence,

$$\Pr[\mathsf{cycle}] = \mathcal{O}\left(\frac{1}{m^2}\right)$$
.



Now, we analyze the probability that a phase is not successful without running into a closed cycle.



### Sequence of visited keys:

$$x = x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_3, x_2, x_1 = x, x_8, x_9, \dots$$

Consider the sequence of not necessarily distinct keys starting with  $\boldsymbol{x}$  in the order that they are visited during the phase.

#### Lemma 11

If the sequence is of length p then there exists a sub-sequence of at least  $\frac{p+2}{3}$  keys starting with x of distinct keys.

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#### Lemma 11

If the sequence is of length p then there exists a sub-sequence of at least  $\frac{p+2}{3}$  keys starting with x of distinct keys.

#### Proof.

Let i be the number of keys (including x) that we see before the first repeated key. Let j denote the total number of distinct keys.

The sequence is of the form:

$$x = x_1 \rightarrow x_2 \rightarrow \cdots \rightarrow x_i \rightarrow x_r \rightarrow x_{r-1} \rightarrow \cdots \rightarrow x_1 \rightarrow x_{i+1} \rightarrow \cdots \rightarrow x_j$$

As  $r \le i - 1$  the length p of the sequence is

$$p = i + r + (j - i) \le i + j - 1$$
.

Either sub-sequence  $x_1 \rightarrow x_2 \rightarrow \cdots \rightarrow x_i$  or sub-sequence  $x_1 \rightarrow x_{i+1} \rightarrow \cdots \rightarrow x_i$  has at least  $\frac{p+2}{2}$  elements.

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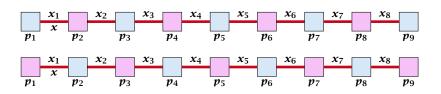
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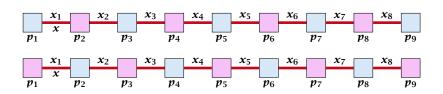
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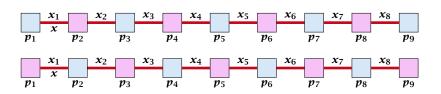
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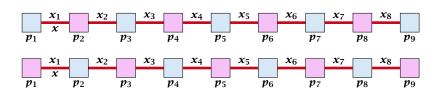




- ightharpoonup s+1 different cells (alternating btw. cells from  $T_1$  and  $T_2$ ).
- ► *s* distinct keys  $x = x_1, x_2, ..., x_s$ , linking the cells.
- ▶ The leftmost cell is either from  $T_1$  or  $T_2$ .



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A path-structure is active if for every key  $x_\ell$  (linking a cell  $p_i$  from  $T_1$  and a cell  $p_j$  from  $T_2$ ) we have

$$h_1(x_\ell) = p_i$$
 and  $h_2(x_\ell) = p_j$ 

#### Observation:

If a phase takes at least t steps without running into a cycle there must exist an active path-structure of size (2t + 2)/3.

The probability that a given path-structure of size s is active is at most  $\frac{\mu^2}{n^{2s}}$ .

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by choosing  $\ell \geq \log{(\frac{1}{2\mu^2m^2})}/\log{(\frac{1}{1+\epsilon})} = \log{(2\mu^2m^2)}/\log{(1+\epsilon)}$ 

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This gives maxsteps =  $\Theta(\log m)$ .

So far we estimated

$$\Pr[\mathsf{cycle}] \leq \mathcal{O}\left(\frac{1}{m^2}\right)$$

and

$$\Pr[\mathsf{unsuccessful} \mid \mathsf{no} \; \mathsf{cycle}] \leq \mathcal{O}(\frac{1}{m^2})$$

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Pr[successful] = Pr[no cycle] - Pr[unsuccessful | no cycle]

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Pr[search at least t steps | successful]

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Pr[search at least *t* steps | successful]

=  $Pr[search at least t steps \land successful] / Pr[successful]$ 

The expected number of complete steps in the successful phase of an insert operation is:

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\begin{split} \Pr[\mathsf{search} \ \mathsf{at} \ \mathsf{least} \ t \ \mathsf{steps} \ | \ \mathsf{successful}] \\ &= \Pr[\mathsf{search} \ \mathsf{at} \ \mathsf{least} \ t \ \mathsf{steps} \ \land \ \mathsf{successful}] / \Pr[\mathsf{successful}] \\ &\leq \frac{1}{c} \Pr[\mathsf{search} \ \mathsf{at} \ \mathsf{least} \ t \ \mathsf{steps} \ \land \ \mathsf{successful}] / \Pr[\mathsf{no} \ \mathsf{cycle}] \end{split}
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Hence,

E[number of steps | phase successful]

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This means the expected cost for a successful phase is constant (even after accounting for the cost of the incomplete step that finishes the phase).

A phase that is not successful induces cost for doing a complete rehash (this dominates the cost for the steps in the phase).

The probability that a phase is not successful is  $q = \mathcal{O}(1/m^2)$  (probability  $\mathcal{O}(1/m^2)$  of running into a cycle and probability  $\mathcal{O}(1/m^2)$  of reaching maxsteps without running into a cycle).

A rehash try requires m insertions and takes expected constant time per insertion. It fails with probability  $p:=\mathcal{O}(1/m)$ .

The expected number of unsuccessful rehashes is  $\sum_{i\geq 1} p^i = \frac{1}{1-p} - 1 = \frac{p}{1-p} = \mathcal{O}(p)$ .

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The probability that a phase is not successful is  $q = O(1/m^2)$ (probability  $\mathcal{O}(1/m^2)$  of running into a cycle and probability  $\mathcal{O}(1/m^2)$  of reaching maxsteps without running into a cycle).

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Let  $Z_i$  denote the event that the i-th rehash occurs:

$$\Pr[Z_i] \le \Pr[\wedge_{j=0}^{i-1} Y_j] \le p^i$$

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Let  $Z_i$  denote the event that the *i*-th rehash occurs:

The 0-th (re)hash is the initial configuration when doing the  $\Pr[Z_i] \leq \Pr[\wedge_{j=0}^{i-1} Y_j] \leq p^i$  insert.

$$\Pr[Z_i] \le \Pr[\wedge_{j=0}^{i-1} Y_j] \le p^i$$

Let  $X_i^s$ ,  $s \in \{1, ..., m+1\}$  denote the cost for inserting the s-th element during the *i*-th rehash (assuming *i*-th rehash occurs):

$$E[X_i^s]$$

Let  $Y_i$  denote the event that the *i*-th rehash does not lead to a valid configuration (assuming i-th rehash occurs) (i.e., one of the m+1 insertions fails):

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$$\begin{split} \mathbf{E}[X_i^s] &= \mathbf{E}[\mathsf{steps} \mid \mathsf{phase} \; \mathsf{successful}] \cdot \Pr[\mathsf{phase} \; \mathsf{sucessful}] \\ &+ \mathsf{maxsteps} \cdot \Pr[\mathsf{not} \; \mathsf{sucessful}] \end{split}$$

### **Formal Proof**

Let  $Y_i$  denote the event that the *i*-th rehash does not lead to a valid configuration (assuming i-th rehash occurs) (i.e., one of the m+1 insertions fails):

$$\Pr[Y_i] \le (m+1) \cdot \mathcal{O}(1/m^2) \le \mathcal{O}(1/m) =: p$$
.

Let  $Z_i$  denote the event that the *i*-th rehash occurs:

The 0-th (re)hash is the initial

configuration when doing the insert. 
$$\Pr[Z_i] \leq \Pr[\wedge_{j=0}^{i-1} Y_j] \leq p^i$$

Let  $X_i^s$ ,  $s \in \{1, ..., m+1\}$  denote the cost for inserting the s-th element during the *i*-th rehash (assuming *i*-th rehash occurs):

$$\begin{split} \mathbf{E}[X_i^s] &= \mathbf{E}[\mathsf{steps} \mid \mathsf{phase} \; \mathsf{successful}] \cdot \Pr[\mathsf{phase} \; \mathsf{sucessful}] \\ &+ \mathsf{maxsteps} \cdot \Pr[\mathsf{not} \; \mathsf{sucessful}] = \mathcal{O}(1) \;\;. \end{split}$$

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#### What kind of hash-functions do we need?

Since maxsteps is  $\Theta(\log m)$  the largest size of a path-structure or cycle-structure contains just  $\Theta(\log m)$  different keys.

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- ▶ Let  $\alpha := 1/(1 + \epsilon)$ .
- Keep track of the number of elements in the table. When  $m \ge \alpha n$  we double n and do a complete re-hash (table-expand).
- Whenever m drops below  $\alpha n/4$  we divide n by 2 and do a rehash (table-shrink).
- Note that right after a change in table-size we have  $m = \alpha n/2$ . In order for a table-expand to occur at least  $\alpha n/2$  insertions are required. Similar, for a table-shrink at least  $\alpha n/4$  deletions must occur.
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#### Lemma 12

Cuckoo Hashing has an expected constant insert-time and a worst-case constant search-time.

Note that the above lemma only holds if the fill-factor (number of keys/total number of hash-table slots) is at most  $\frac{1}{2(1+\epsilon)}$ .

The  $1/(2(1+\epsilon))$  fill-factor comes from the fact that the total hash-table is of size 2n (because we have two tables of size n); moreover  $m \le (1+\epsilon)n$ .

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