# Hash Tables: Linear Probing 

Uri Zwick Tel Aviv University

# Hashing with open addressing "Uniform probing" 

Hash table of size $m$
Assume that $h: U \times[m] \rightarrow[m]$
Insert key $k$ in the first free position among $h(k, 0), h(k, 1), h(k, 2), \ldots, h(k, m-1)$
(Sometimes) assumed to be a permutation


Table is not full $\rightarrow$ Insertion succeeds To search, follow the same order

## Linear probing

"The most important hashing technique"

$$
h(k, i)=(h(k)+i) \bmod m
$$



More probes than uniform probing due to clustering:
long runs tend to get longer and merge with other runs
But, many fewer cache misses
Extremely efficient in practice
How do we analyze it?
Which hash functions should we use?

## Order of insertions



Theorem: The set of occupied cell and the total number of probes done while inserting a set of items into a hash table using linear probing does not depend on the order in which the items are inserted

## Exercise: Prove the theorem

Exercise: Is the same true for uniform probing?

## Number of probes

Exercise: Show that if, after inserting $n$ items into a table of size $m$, the occupied cells in the table form runs of length $\ell_{1}, \ell_{2}, \ldots$, where $\sum_{i} \ell_{i}=n$, then the expected number of probes in an unsuccessful search, assuming the searched key is mapped into a uniformly random location in the table, is

$$
1+\frac{1}{m} \sum_{i} \frac{\ell_{i}\left(\ell_{i}+1\right)}{2}
$$

Exercise: What are the smallest and largest possible total number of probes needed to construct a hash table that contain runs of length $\ell_{1}, \ell_{2}, \ldots$ ?

## Probabilistic analysis of uniform probing [Petersen (1957)]

$n$ - number of elements in table $m$ - size of hash table
$\alpha=n / m-$ load factor (Note: $\alpha \leq 1$ )
Uniform probing: for every $k \in U$, $h(k, 0), \ldots, h(k, m-1)$ is random permutation, independent of all other permutations
Expected no. of probes in an unsuccessful search of a random item is at most


Expected no. of probes in a successful search is at most

$$
\frac{1}{\alpha} \ln \frac{1}{1-\alpha}
$$

## Probabilistic analysis of uniform probing [Petersen (1957)]

Claim: Expected no. of probes in an unsuccessful search is at most:


The probability that a random cell is occupied is $\alpha$
The probability that the first $i$ cells probed are all occupied is at most $\alpha^{i}$

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

Exercise: Do the calculation more carefully and show that the expected no. of probes in an unsuccessful search is exactly $(m+1) /(m-n+1)$

## Probabilistic analysis of linear probing

 [Knuth (1962)]$$
\alpha=n / m-\operatorname{load} \text { factor }(\alpha \leq 1)
$$

## Random hash function:

for every $k \in U, h(k)$ is uniformly distributed, independent of all other $h\left(k^{\prime}\right)$, for $k \neq k^{\prime}$

Expected no. of probes in an unsuccessful search is at most

$$
\frac{1}{2}\left(1+\left(\frac{1}{1-\alpha}\right)^{2}\right)
$$

Expected no. of probes in a successful search of a random item is at most

$$
\frac{1}{2}\left(1+\frac{1}{1-\alpha}\right)
$$

## Expected number of probes Assuming random hash functions



When, say, $\alpha \leq 0.6$, all small constants

## Expected number of probes



# Probabilistic analysis of linear probing [Knuth (1962)] 

$n$ - number of elements in table $m$ - size of hash table

What is the probability that $T[0]$ is empty?

$$
1-\frac{n}{m}
$$

By symmetry, all cells are equally likely to be empty

What is the probability that
$T[0], T[k+1]$ empty, $T[1], \ldots, T[k]$ occupied?

$\binom{n}{k}\left(\frac{k+1}{m}\right)^{k}\left(1-\frac{k}{k+1}\right)\left(\frac{m-k-1}{m}\right)^{n-k}\left(1-\frac{n-k}{m-k-1}\right)$
Exactly $k$ items should be mapped to [ $0, k$ ] and $n-k$ items should be mapped to $[k+1, m-1]$

Given that $k$ items are mapped to $[0, k]$, $T[0]$ should remain empty
Given that $n-k$ items are mapped to $[k+1, m-1]$, $T[k+1]$ should remain empty

What is the probability that
$T[0], T[k+1]$ empty, $T[1], \ldots, T[k]$ occupied?

$\binom{n}{k}\left(\frac{k+1}{m}\right)^{k}\left(1-\frac{k}{k+1}\right)\left(\frac{m-k-1}{m}\right)^{n-k}\left(1-\frac{n-k}{m-k-1}\right)$
$\preccurlyeq$
$g_{k}=m^{-n}\binom{n}{k}(k+1)^{k-1}(m-k-1)^{n-k-1}(m-n-1)$
$g_{k}$ is the probability that a run of size exactly $k$ starts at a given position

Exercise: $g_{0} \rightarrow(1-\alpha) \mathrm{e}^{-\alpha}, g_{1} \rightarrow \alpha(1-\alpha) \mathrm{e}^{-2 \alpha}$

What is the probability that an unsuccessful search encounters exactly $k$ occupied cells?


$$
p_{k}=\sum_{i=k}^{n} g_{i}
$$

Interesting to note that

$$
\begin{gathered}
p_{0}=1-\alpha \\
p_{1}=p_{0}-g_{0} \rightarrow(1-\alpha)\left(1-\mathrm{e}^{-\alpha}\right)
\end{gathered}
$$

The expected no. of probes in an unsuccessful search, which is also the expected no. of probes needed to insert the $(n+1)$-st item is

$$
C_{n}^{\prime}=\sum_{k=0}^{n}(k+1) p_{k}=\sum_{k=0}^{n}\binom{k+2}{2} g_{k}
$$

$$
\begin{gathered}
C_{n}^{\prime}=\sum_{k=0}^{n}(k+1) p_{k}=\sum_{k=0}^{n}\binom{k+2}{2} g_{k} \\
=\frac{1}{2}(\underbrace{\left.\sum_{k=0}^{n}(k+1) g_{k}+\sum_{k=0}^{n}(k+1)^{2} g_{k}\right)}_{k=0} \\
\sum_{k=0}^{n} p_{k}=1 \quad Q_{1}(m, n) \\
Q_{1}(m, n)=m^{-n} \sum_{k=0}^{n}\binom{n}{k}(k+1)^{k+1}(m-k-1)^{n-k-1}(m-n-1) \\
\text { Ex. 6.4.27 }
\end{gathered}
$$



Abel's binomial theorem (see Knuth Eq. 1.2.6-(16))

$$
(x+y)^{n}=\sum_{k=0}^{n}\binom{n}{k} x(x-k z)^{k-1}(y+k z)^{n-k}
$$

## Unsuccessful search

$$
\begin{gathered}
C_{n}^{\prime}=\frac{1}{2}\left(1+Q_{1}(m, n)\right) \\
Q_{1}(m, n)=\sum_{k=0}^{n}(k+1) \frac{(n)_{k}}{m^{k}} \leq \sum_{k=0}^{n}(k+1)\left(\frac{n}{m}\right)^{k}<\left(\frac{1}{1-\alpha}\right)^{2} \\
(n)_{k}=n(n-1) \ldots(n-k+1) \leq n^{k} \\
\sum_{k \geq 0}(k+1) \alpha^{k}=\left(\frac{1}{1-\alpha}\right)^{2}
\end{gathered}
$$

The birth of Knuth's style Analysis of Algorithms...

## Successful search / Construction time

The expected number of probes in a search of randomly selected item is

$$
C_{n}=\frac{1}{n} \sum_{k=0}^{n-1} C_{k}^{\prime}<\frac{1}{2}\left(1+\frac{1}{1-\alpha}\right)
$$

The expected number of probes in the construction of the table is

$$
n C_{n}=\sum_{k=0}^{n-1} C_{k}^{\prime}
$$

# The "parking problem" <br> [Knuth (1962)] [Konheim-Weiss (1966)] 

A one-way street contains $m$ parking spots $n$ cars arrive, one after the other
The $i-t h$ car chooses a random number $h_{i}$ between 1 and $m$ and parks in the first free spot at or after location $h_{i}$, if there is one
Exercise: What is the probability that all cars find a parking spot?

## Linear Probing: Theory vs. Practice

In practice, we cannot use a truly random hash function

Does linear probing still have a constant expected time per operation when more realistic hash functions are used?

For chaining, 2-independence, or just "universality", was enough

How much independence is needed for linear probing?

## Linear Probing: Theory vs. Practice

5-independence suffices for linear probing!
[Pagh-Pagh-Rŭzíc (2009)]

4-independence does not suffice!
[Pătraşcu-Thorup (2010)]

## $k$-independence

## Definition:

$X_{1}, X_{2}, \ldots, X_{k}$ are independent iff
for every $x_{1}, x_{2}, \ldots, x_{k}$, we have

$$
\begin{gathered}
\operatorname{Pr}\left[X_{1}=x_{1}, X_{2}=x_{2}, \ldots, X_{k}=x_{k}\right]= \\
\operatorname{Pr}\left[X_{1}=x_{1}\right] \operatorname{Pr}\left[X_{2}=x_{2}\right] \ldots \operatorname{Pr}\left[X_{k}=x_{k}\right]
\end{gathered}
$$

## Definition:

$X_{1}, X_{2}, \ldots, X_{n}$ are $k$-independent iff for every distinct $i_{1}, i_{2}, \ldots, i_{k}, X_{i_{1}}, X_{i_{2}}, \ldots, X_{i_{k}}$ are independent

## Families of $k$-independent hash functions

Let $H$ be a family of hash functions from $U$ to $V$. $H$ is $k$-independent iff for every distinct $x_{1}, x_{2}, \ldots, x_{k} \in U, h\left(x_{1}\right), h\left(x_{2}\right), \ldots, h\left(x_{k}\right)$ are independent, when $h$ is chosen at random from $H$

We usually require that for every $x \in U$, $h(x)$ is (almost) uniformly distributed on $V$

If $H$ is $k$-independent and $H^{\prime}=\{f(h(x)) \mid h \in H\}$, for some function $f$, then $H^{\prime}$ is also $k$-independent

## Polynomial hash functions

Lemma: If $F$ is a field, then

$$
H=\left\{\sum_{i=0}^{k-1} a_{i} x^{i} \mid a_{0}, a_{1}, \ldots, a_{k} \in F\right\}
$$

is a $k$-independent family of hash functions
Corollary: If $p$ is a prime, and $m$ is arbitrary, then $H=\left\{\left(\left(\sum_{i=0}^{k-1} a_{i} x^{i}\right) \bmod p\right) \bmod m \mid a_{0}, a_{1}, \ldots, a_{k} \in F\right\}$ is a $k$-independent family of hash functions

When $p \gg m, h(x)$ is almost uniformly
distributed on $[m]=\{0,1, \ldots, m-1\}$

## Polynomial hash functions

$$
h(x)=\sum_{i=0}^{k-1} a_{i} x^{i}
$$

## $x_{1}, x_{2}, \ldots, x_{k} \in F$ distinct

$y_{1}, y_{2}, \ldots, y_{k} \in F$ (not necessarily distinct)

$$
h\left(x_{1}\right)=y_{1}, h\left(x_{2}\right)=y_{2}, \ldots, h\left(x_{k}\right)=y_{k}
$$

$$
\left(\begin{array}{cccc}
1 & x_{1} & \ldots & x_{1}^{k-1} \\
1 & x_{2} & \ldots & x_{2}^{k-1} \\
\vdots & \vdots & \ddots & \vdots \\
1 & x_{k} & \ldots & x_{k}^{k-1}
\end{array}\right)\left(\begin{array}{c}
a_{0} \\
a_{1} \\
\vdots \\
a_{k-1}
\end{array}\right)=\left(\begin{array}{c}
y_{1} \\
y_{2} \\
\vdots \\
y_{k}
\end{array}\right)
$$

Unique solution!

## Vandermonde Determinant

$$
\operatorname{det}\left(\begin{array}{cccc}
1 & x_{1} & \ldots & x_{1}^{k-1} \\
1 & x_{2} & \ldots & x_{2}^{k-1} \\
\vdots & \vdots & \ddots & \vdots \\
1 & x_{k} & \ldots & x_{k}^{k-1}
\end{array}\right)=\prod_{i<j}\left(x_{j}-x_{i}\right)
$$

## Tabulation-based hash functions [Carter-Wegman (1979)] [Pătraşcu-Thorup (2010)]

$$
\begin{gathered}
h\left(x_{1}, x_{2}, \ldots, x_{c}\right)=h_{1}\left(x_{1}\right) \oplus h_{2}\left(x_{2}\right) \oplus \cdots \oplus h_{c}\left(x_{c}\right) \\
h_{1}, h_{2}, \ldots, h_{c}:\left[u^{1 / c}\right] \rightarrow\left[2^{k}\right] \\
h:[u] \rightarrow\left[2^{k}\right] \\
{[u]=\{0,1, \ldots, u-1\}}
\end{gathered}
$$

$h_{1}, h_{2}, \ldots, h_{c}$ may be implemented using small look-up tables
Very efficient in practice

## Tabulation-based hash functions [Carter-Wegman (1979)] [Pătraşcu-Thorup (2010)]

$$
h\left(x_{1}, x_{2}, \ldots, x_{c}\right)=h_{1}\left(x_{1}\right) \oplus h_{2}\left(x_{2}\right) \oplus \cdots \oplus h_{c}\left(x_{c}\right)
$$

If $h_{1}, h_{2}, \ldots, h_{c}$ are independently chosen from a uniform 2-independent family, then $h$ is 2-independent

If $h_{1}, h_{2}, \ldots, h_{c}$ are independently chosen from a uniform 3-independent family, then $h$ is 3-independent

Not 4-independent!

$$
h\left(x_{1}, y_{1}\right) \oplus h\left(x_{1}, y_{2}\right) \oplus h\left(x_{2}, y_{1}\right) \oplus h\left(x_{2}, y_{2}\right)=0
$$

## Tabulation-based hash functions [Thorup-Zhang (2012)]

$$
h(x, y)=h_{1}(x) \oplus h_{2}(y) \oplus h_{3}(x+y)
$$

If $h_{1}, h_{2}, h_{3}$ are independently chosen from a 5 -independent family, then $h$ is 5-independent

Higher independence possible at the cost of more table look-ups

Linear probing with bounded independence [Pagh-Pagh-Rŭzíc (2009)] [Pătraşcu-Thorup (2010)]

| Independence | $\mathbf{2}$ | $\mathbf{3}$ | $\mathbf{4}$ | $\mathbf{5}$ |
| :---: | :---: | :---: | :---: | :---: |
| Search time | $\Theta(\sqrt{n})$ | $\Theta(\log n)$ | $\Theta(1)$ |  |
| Construction time | $\Theta(n \log n)$ | $\Theta(n)$ |  |  |

Upper bounds hold for any set of keys and any family with the specified independence

Lower bounds hold for some sets of keys and some families with the specified independençe

## Balls in Bins

Throw $n$ balls randomly into $m$ bins


All throws are uniform and (partially-)independent

## Balls in Bins

## Throw $n$ balls randomly into $m$ bins

Let $X$ be the number of balls that fall into a specific bin, e.g., the first

Let $X_{i}$ be 1 if the $i$-th ball falls into the specific bin, and 0 otherwise

We want to bound the probability that $X$ is large


## Tail bounds

Markov's inequality:

$$
\text { If } X \geq 0, \operatorname{Pr}[X \geq b \mu] \leq \frac{1}{b}
$$

Chebyshev's inequality:

$$
\begin{gathered}
\operatorname{Pr}[|\mathrm{X}-\mu| \geq b \mu]=\operatorname{Pr}\left[(X-\mu)^{2} \geq b^{2} \mu^{2}\right] \\
\leq \frac{E\left[(X-\mu)^{2}\right]}{b^{2} \mu^{2}}=\frac{\operatorname{Var}[X]}{b^{2} \mu^{2}}
\end{gathered}
$$

Higher (even) moments:

$$
\begin{aligned}
& \operatorname{Pr}[|\mathrm{X}-\mu| \geq b \mu]=\operatorname{Pr}\left[(X-\mu)^{k} \geq b^{k} \mu^{k}\right] \\
& \quad \leq \frac{E\left[(X-\mu)^{k}\right]}{b^{k} \mu^{k}}=\frac{M_{k}[X-\mu]}{b^{k} \mu^{k}}
\end{aligned}
$$

## Tail bounds

## Chernoff bound:

If $X_{1}, X_{2}, \ldots, X_{n}$ are independent indicators, $X=\sum_{i=1}^{n} X_{i}, \mu=E[X]$, and $\delta>0$, then

$$
\operatorname{Pr}[X \geq(1+\delta) \mu]<\left(\frac{e^{\delta}}{(1+\delta)^{1+\delta}}\right)^{\mu}
$$

Proof: Apply Markov's inequality to $e^{t X}$ and choose $t=\ln (1+\delta)$

Chernoff bound is stronger.
But it requires complete independence.

## Computing moments

$$
\begin{gathered}
X=\sum_{i=1}^{n} X_{i} \\
\mu=E[X]=n p \\
X-\mu=\sum_{i=1}^{n} Y_{i} \quad Y_{i}=\left\{\begin{array}{lll}
1 & \text { w. p. } & p \\
0 & \text { w. p. } 1-p
\end{array}\right. \\
E\left[Y_{i}\right]=0 \\
E\left[(X-\mu)^{k}\right]=E\left[\left(\sum_{i=1}^{n} Y_{i}\right)^{k}\right] \\
\quad=E\left[\sum_{i_{1}, i_{2}, \ldots, i_{k}} Y_{i_{1}} Y_{i_{2}} \ldots Y_{i_{k}}\right] \\
\quad=\sum_{i_{1}, i_{2}, \ldots, i_{k}} E\left[Y_{i_{1}} Y_{i_{2}} \ldots Y_{i_{k}}\right] \\
E\left[Y_{i_{1}} Y_{i_{2}} \ldots Y_{i_{k}}\right] \stackrel{?}{=} E\left[Y_{i_{1}}\right] E\left[Y_{i_{2}}\right] \ldots E\left[Y_{i_{k}}\right]
\end{gathered}
$$

## Computing moments

If $X_{1}, X_{2}, \ldots, X_{n}$ are $k$-independent, then so are $Y_{1}, Y_{2}, \ldots, Y_{n}$

If $i_{1}, i_{2}, \ldots, i_{k}$ are distinct, then

$$
E\left[Y_{i_{1}} Y_{i_{2}} \ldots Y_{i_{k}}\right]=E\left[Y_{i_{1}}\right] E\left[Y_{i_{2}}\right] \ldots E\left[Y_{i_{k}}\right]=0
$$

If $i_{1}$ differs from $i_{2}, \ldots, i_{k}$, then

$$
E\left[Y_{i_{1}} Y_{i_{2}} \ldots Y_{i_{k}}\right]=E\left[Y_{i_{1}}\right] E\left[Y_{i_{2}} \ldots Y_{i_{k}}\right]=0
$$

$$
\text { If } i \neq j \text {, then }
$$

$$
E\left[Y_{i} Y_{i} Y_{j} Y_{j}\right]=E\left[Y_{i}^{2}\right] E\left[Y_{j}^{2}\right]
$$

## Computing moments

$$
Y_{i}=\left\{\begin{array}{cc}
1-p \quad \text { w. p. } & p \\
-p & \text { w. p. } \\
\hline
\end{array}\right.
$$

$$
\begin{gathered}
E\left[Y_{i}^{k}\right]=p(1-p)^{k}+(1-p)(-p)^{k} \\
=p(1-p)\left((1-p)^{k-1}-(-p)^{k-1}\right) \\
\leq p(1-p) \leq p
\end{gathered}
$$

If $X_{1}, X_{2}, \ldots, X_{n}$ are 2 -independent

$$
\begin{aligned}
& E\left[(X-\mu)^{2}\right]=E\left[\left(\sum_{i=1}^{n} Y_{i}\right)^{2}\right] \\
= & \sum_{i=1}^{n} E\left[Y_{i}^{2}\right]=n p(1-p)<\mu
\end{aligned}
$$

## Computing moments

If $X_{1}, X_{2}, \ldots, X_{n}$ are 4-independent

$$
E\left[(X-\mu)^{4}\right]=E\left[\left(\sum_{i=1}^{n} Y_{i}\right)^{4}\right]
$$

$$
=3 \sum_{i \neq j} E\left[Y_{i}^{2}\right] E\left[Y_{j}^{2}\right]+\sum_{i} E\left[Y_{i}^{4}\right]
$$

$$
\leq 3 n^{2} p^{2}+n p=3 \mu^{2}+\mu
$$

If $X_{1}, X_{2}, \ldots, X_{n}$ are $k$-independent,
where $k=O(1)$ and $\mu=\Omega(1)$, then

$$
E\left[(X-\mu)^{k}\right]=O\left(\mu^{k / 2}\right)
$$

(We only need 4-th moments)

## Planting a binary tree



## Crowded nodes [Pătraşcu-Thorup (2010)]



## Simplifying assumptions:

 $m$ is a power of 2$$
\alpha=n / m \leq 2 / 3
$$

A node at height $i$ corresponds to $2^{i}$ consecutive cells in the table
A node at height $i$ is crowded, if at least $(3 / 4) 2^{i}$ items are mapped into its interval

The final locations of items mapped into an interval may be outside the interval

## Simple observation I



## Simple observation II



## Main observation [Pătraşcu-Thorup (2010)]

Consider a run of length $2^{i} \leq \ell$, where $i>2$
At least one of the first four nodes at level $i-2$
whose last cell belongs to the run is crowded


## Proof of main observation

Just before the run, there is an empty cell. Thus, if 1 is not crowded, it contributes less than $(3 / 4) 2^{i-2}$ items to the run If $2,3,4$ are not crowded, then each of their intervals can absorb at least $(1 / 4) 2^{i-2}$ items
Thus, if none of $1,2,3,4$ is crowded, the run ends at or before the interval of 4 and its length is less than $4 \cdot 2^{i-2}=2^{i}$


## Probability of being crowded

Assume that $\alpha=\frac{n}{m} \leq \frac{2}{3}$
Consider a node at height $i$
Throwing $n$ balls into $m / 2^{i}$ bins

$$
\begin{gathered}
\mu=n /\left(m / 2^{i}\right)=\alpha 2^{i} \leq(2 / 3) 2^{i} \\
\operatorname{Pr}\left[\mathrm{X} \geq \frac{3}{4} 2^{i}\right] \leq \operatorname{Pr}[|\mathrm{X}-\mu| \geq b \mu] \\
\leq \frac{E\left[(X-\mu)^{k}\right]}{b^{k} \mu^{k}}=O\left(\frac{1}{b^{k} \mu^{k / 2}}\right)=O\left(2^{-i k / 2}\right) \\
b \geq(3 / 4-\alpha) / \alpha \geq 3 / 24
\end{gathered}
$$

## Construction time [Pătraşcu-Thorup (2010)]

Let $\ell_{1}, \ell_{2}, \ldots$, where $\sum_{i} \ell_{i}=n$, be the length of the consecutive runs in the table after inserting the $n$ items

The cost of the construction is at most $\sum_{i} \ell_{i}^{2}$
Runs of length $\ell_{i}<4$ contribute only $O(n)$
By the main observation, if $2^{i} \leq \ell_{i}<2^{i+1}$, then at least one of the first four nodes at level $i-2$ whose last cell is in the run is crowded.
Each node corresponds to at most one run.

$$
\sum_{i} \ell_{i}^{2}=O\left(\sum_{v} 2^{2 \cdot \operatorname{height}(v)}[v \text { crowded }]\right)
$$

## Construction time [Pătraşcu-Thorup (2010)]

$$
\begin{aligned}
& E\left[\sum_{i} \ell_{i}^{2}\right]=O\left(\sum_{v} 2^{2 \cdot h \operatorname{height}(v)} \operatorname{Pr}[v \text { crowded }]\right) \\
& =O\left(\sum_{i=0}^{\log _{2} m} \frac{m}{2^{i}} 2^{2 i} 2^{-\frac{k i}{2}}\right)=O\left(n \sum_{i=0}^{\log _{2} m} 2^{i} 2^{-\frac{k i}{2}}\right)
\end{aligned}
$$

$$
\begin{aligned}
& \text { If } k=2 \text {, we get } O(n \log n) \\
& \quad \text { If } k=4, \text { we get } O(n)
\end{aligned}
$$

## Query time (successful/unsuccessful) [Pătraşcu-Thorup (2010)]

If $h(k)$ is in a run of length $\ell$, then the search time is $O(\ell)$

If $h(k)$ is in a run of length $2^{i} \leq \ell<2^{i+1}$, then at least one of 12 nodes at height $i-2$ associated with $h(k)$ is crowded

$$
\begin{gathered}
p(i)=\operatorname{Pr}[v \text { crowded }]=O\left(2^{-i k^{\prime} / 2}\right), \text { height }(v)=i \\
E[\ell] \leq 3+12 \sum_{i \geq 2} p(i-2) \cdot 2^{i+1}
\end{gathered}
$$

## Query time (successful/unsuccessful) [Pătraşcu-Thorup (2010)]

$$
E[\ell] \leq 3+12 \sum_{i \geq 2} p(i-2) \cdot 2^{i+1}=O\left(\sum_{i=0}^{\log _{2} m} 2^{i} 2^{-k^{\prime} i / 2}\right)
$$

$k^{\prime}$ - The independence after conditioning on the hash value of the key searched

$$
\begin{gathered}
k^{\prime}=k-1 \\
\text { If } k=2 \text {, we get } O(\sqrt{n}) \\
\text { If } k=3 \text {, we get } O(\log n) \\
\text { If } k=5 \text {, we get } O(1)
\end{gathered}
$$

## Why $12 ?$

The constant 12 itself, of course, if not too important. The important thing is that it is a constant


