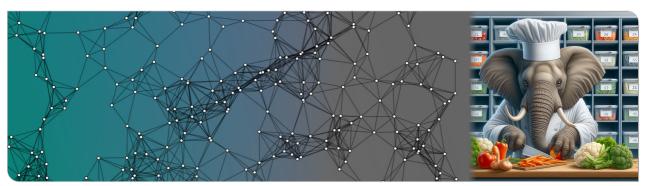




Probability and Computing – Classic Hash Tables

Stefan Walzer, Maximilian Katzmann | WS 2023/2024



Prüfungsanmeldung



- Am einfachsten: Hier angeben, wann ihr Zeit habt: https://www.terminplaner.dfn.de/W4m8QyA9vvp1K19m
- Alternativ: Email an Stefan und Max.
- Wir bieten euch dann einen Termin per Email an.

Content



- 1. Conceptions: What is a Hash Function?
 - Hashing in the Wild
 - What should a Theorist do?
- 2. Use Case 1: Hash Table with Chaining
 - Using SUHA
 - Using Universal Hashing
- 3. Use Case 2: Linear Probing
 - Using SUHA
 - Using Universal Hashing
- 4. Conclusion

Hash Table with Chaining

e.g. std::unordered_set, java.util.HashMap



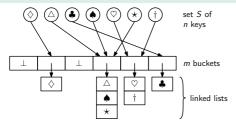
Terminology

Universe (or domain) of *keys* (strings, integers, game states in chess)

 $S \subseteq D$: set of *n* keys (possibly with associated data)

 $h: D \to R$: hash function, range usually R = [m]

 $\alpha = \frac{n}{m}$: load factor, $\alpha \leq \alpha_{\text{max}} = \mathcal{O}(1)$



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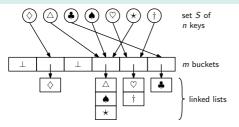
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Goal

Operations in time t with $\mathbb{E}[t] = \mathcal{O}(1)$. Randomness comes from the hash function.

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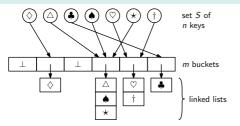
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Operations in time t with $\mathbb{E}[t] = \mathcal{O}(1)$. Randomness comes from the hash function.

Ideal Hash Functions

Every function from *D* to *R* is equally likely to be *h*.

Conceptions: What is a Hash Function?

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Ideal Hash Functions are Impractical



Naive Idea

- Let R^D denote all functions from D to R. We pick $h \sim \mathcal{U}(R^D)$.
- There are |R| options for the hash of each $x \in D$
- Hence: $|R^D| = |R|^{|D|}$

Why $h \sim \mathcal{U}(R^D)$ is desirable

- $h \sim \mathcal{U}(R^D) \Leftrightarrow \forall x_1, \dots, x_n \in D : h(x_1), h(x_2), \dots, h(x_n)$ are *independent* and uniformly random in R.
- In particular: $\forall x_1, \ldots, x_n \in D, \forall i_1, \ldots, i_n : \Pr_{h \sim \mathcal{U}(R^D)}[h(x_1) = i_1 \wedge \ldots \wedge h(x_n) = i_n] = |R|^{-n}$.

Why $h \sim \mathcal{U}(R^D)$ is unwieldy

 $\log_2(|R|^{|D|}) = |D| \cdot \log_2(|R|)$ bits to store $h \sim \mathcal{U}(R^D)$

 \rightarrow for $D = \{0, 1\}^{64}$: more than 2^{64} bits.

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

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(it depends on who you ask)



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Cryptographic Hash Function

A **collision resistant** function such as h = sha256sum

\$ sha256sum myfile.txt

018a7eaee8a...3e79043e21ab4 myfile.txt

Range $R = \{0, 1\}^{256}$. It is hard to find x, y with h(x) = h(y).

 \hookrightarrow Files with equal hashes are likely the same.

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Cryptographic Pseudorandom Function

A function f: Seeds \times $D \to R$ where $\log_2 |\text{Seeds}|$ is small and no efficient algorithm can distinguish

- $f(s,\cdot)$ for $s \sim \mathcal{U}(\text{Seeds})$ and
- $h(\cdot)$ for $h \sim \mathcal{U}(R^D)$,

except with negligible probability.

Conceptions: What is a Hash Function?

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Hash Function in Algorithm Engineering

- typically small range $|R| = \mathcal{O}(n)$
- should behave like $h \sim \mathcal{U}(R^D)$ in my application
- should be fast to evaluate

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- typically small range $|R| = \mathcal{O}(n)$ ⇔ cannot be collision resistant
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- adversarial settings rarely considered

Use Case 2: Linear Probing

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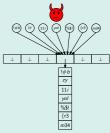
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HashDoS is a thing.



Use Case 2: Linear Probing

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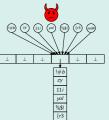
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- should be fast to evaluate
- adversarial settings rarely considered, although:

HashDoS is a thing. However: Hash function and hash values need not be public.



Use Case 2: Linear Probing

Conclusion

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Hashing in Practice

Black Magic, do not touch!



MurmurHash

```
Bitshifts, Magic Constants, ...
uint32 t murmur3 32(const uint8 t* kev.
           size t len, uint32 t seed) {
    uint32 t h = seed:
    uint32 t k:
    for (size t i = len >> 2: i: i--) {
       memcpy(&k, key, sizeof(uint32_t));
       kev += sizeof(uint32 t):
       h ^= murmur 32 scramble(k):
       h = (h \ll 13) \mid (h \gg 19):
       h = h * 5 + 0xe6546b64:
    1...1
    return h:
static inline uint32_t murmur_32_scramble(uint32_t k) {
    k = 0xcc9e2d51:
    k = (k \ll 15) | (k \gg 17);
    k *= 0x1b873593;
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Usage

For R = [m], pick seed $\sim \mathcal{U}(\{0,1\}^{32})$ and use

$$h(x) = \text{murmur3}_{32}(x, \text{seed}) \mod m$$
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(should avoid modulo in practice, see https://github.com/lemire/fastrange)

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Does *h* behave like a random function?

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YES, with respect to many statistical tests.

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- NO. HashDoS attacks are known.
 - See https://en.wikipedia.org/wiki/MurmurHash#Vulnerabilities
- MAYBE, for your favourite application.

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Approach 1: Ignore the Problem



Simple Uniform Hashing Assumption (SUHA)

- We have access to $h \sim \mathcal{U}(R^D)$ for any R and D.
- h takes $\mathcal{O}(1)$ time to evaluate.
- h takes no space to store.

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How to Analyse your Algorithm

- Assume SUHA holds.
- Analyse algorithm under SUHA.
- Hope that algorithm still works with real hash functions.

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Modelling assumption.

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- Modelling assumption.
- Excellent track record in non-adversarial settings.

Conceptions: What is a Hash Function? 0000000

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Approach 2: Bring your own Hash Functions



Analyse Algorithm using Universal Hashing

Define family $\mathcal{H} \subseteq R^D$ of hash functions with $\log(|\mathcal{H}|)$ not too large.

 \hookrightarrow sampling and storing $h \in \mathcal{H}$ is cheap

Proof that algorithm with $h \sim \mathcal{U}(\mathcal{H})$ has good expected behaviour.

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Remarks

Conceptions: What is a Hash Function?

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- Rigorously covers non-adversarial settings.

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- Proof that algorithm with $h \sim \mathcal{U}(\mathcal{H})$ has good expected behaviour.

Remarks

- lacktriangle Mathematical structure of ${\cal H}$ must be amenable to analysis.
- Rigorously covers non-adversarial settings.
- Proofs often difficult.
 - → Wider theory practice gap than with SUHA.

Conceptions: What is a Hash Function?

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Approach 3: Let the Cryptographers do the Work



How to Analyse your Algorithm using Cryptographic Assumptions

- 1 Analyse algorithm under SUHA.
- 2 Actually use cryptographic pseudorandom function f.
 - **Case 1:** Everything still works. Great! :-)
 - Case 2: Something fails.
 - \Rightarrow Your use case can tell the difference between f and true randomness.
 - \hookrightarrow The cryptographers said this is impossible. ${\it 1}$

Approach 3: Let the Cryptographers do the Work



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Should we use cryptographic pseudorandom functions?

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Should we use cryptographic pseudorandom functions?

- YES. Algorithms become robust even in some adversarial settings.

https://en.wikipedia.org/wiki/SipHash

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NO. Too slow in high-performance settings.

Hash Function	MiB / sec
SipHash	944
Murmur3F	7623
xxHash64	12109

(source: https://github.com/rurban/smhasher)

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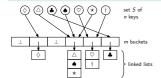
- 1. Conceptions: What is a Hash Function?
 - Hashing in the Wild
 - What should a Theorist do?
- 2. Use Case 1: Hash Table with Chaining
 - Using SUHA
 - Using Universal Hashing
- 3. Use Case 2: Linear Probing
 - Using SUHA
 - Using Universal Hashing
- 4. Conclusion



Search Time under Chaining

$$\max_{S\subseteq D} \max_{x\in D} |S|=n$$

$$1 + |\{y \in S \mid h(y) = h(x)\}|$$



Conceptions: What is a Hash Function?

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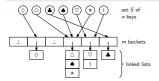
Conclusion 000



Search Time under Chaining

For $n, m \in \mathbb{N}$ and a family $\mathcal{H} \subseteq [m]^D$ of hash functions the *maximum expected search time* is at most

$$T_{\text{chaining}}(n, m, \mathcal{H}) = \max_{\substack{S \subseteq D \\ |S| = n}} \max_{x \in D} \mathbb{E}_{h \sim \mathcal{U}(\mathcal{H})} \Big[1 + |\{y \in S \mid h(y) = h(x)\}| \Big]$$



Conceptions: What is a Hash Function?

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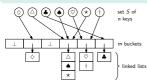


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 $\angle!$ Key set is worst case. Only $h \in \mathcal{H}$ is random. Key set is fixed before h is chosen.



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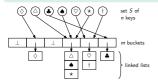


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 \triangle Key set is *worst case*. Only $h \in \mathcal{H}$ is random. Key set is fixed *before h* is chosen.



Theorem: Hash Table with Chaining under SUHA

If
$$\mathcal{H} = [m]^D$$
 then $T_{\text{chaining}}(n, m, \mathcal{H}) \leq 2 + \alpha = \mathcal{O}(1)$ if $\alpha \in \mathcal{O}(1)$.

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Use Case 1: Hash Table with Chaining ○●○○○○○

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Theorem: Hash Table with Chaining under SUHA

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, $S \subseteq D$ with $|S| = n$ and $x \in D$ then

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$$= 1 + \sum_{y \in S} \Pr_{h \sim \mathcal{U}(\mathcal{H})}[h(y) = h(x)]$$
$$= 1 + 1 + \sum_{y \in S \setminus \{x\}} \Pr_{h \sim \mathcal{U}(\mathcal{H})}[h(y) = h(x)]$$

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining 00000000

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Proof.

$$\begin{split} &\mathbb{E}_{h \sim \mathcal{U}(\mathcal{H})} \Big[1 + |\{ y \in S \mid h(y) = h(x) \}| \Big] \\ &= \mathbb{E}_{h \sim \mathcal{U}(\mathcal{H})} \Big[1 + \sum_{y \in S} \mathbb{1}_{\{h(y) = h(x)\}} \Big] \\ &= 1 + \sum_{y \in S} \mathbb{P}_{r_{h \sim \mathcal{U}(\mathcal{H})}} [h(y) = h(x)] \\ &= 1 + \sum_{y \in S \setminus \{x\}} \mathbb{P}_{r_{h \sim \mathcal{U}(\mathcal{H})}} [h(y) = h(x)] \\ &= 1 + \sum_{y \in S \setminus \{x\}} \mathbb{E}_{h \sim \mathcal{U}(\mathcal{H})} \Big[\mathbb{1}_{\{h(y) = h(x)\}} \Big] \\ &= 2 + \sum_{y \in S \setminus \{x\}} \frac{1}{m} \leq 2 + \frac{n}{m} = 2 + \alpha. \quad \Box \end{split}$$

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Definition: c-universal hash family

A class
$$\mathcal{H} \subseteq [m]^D$$
 is called *c-universal* if: $\forall x \neq y \in D : \Pr_{h \sim \mathcal{U}(\mathcal{H})}[h(x) = h(y)] \leq \frac{c}{m}$.

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Note: $\mathcal{H} = [m]^D$ is 1-universal.



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Reminder (?): Finite Fields

Let $\mathbb{F}_p = \{0, \dots, p-1\}$ for a prime number p. Then $(\mathbb{F}_p, \times, \oplus)$ is a field where

$$a \times b := (a \cdot b) \mod p$$
 and $a \oplus b := (a + b) \mod p$.

In particular $(\mathbb{F}_p^* := \mathbb{F}_p \setminus \{0\}, \times)$ is a group.



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The class of Linear Hash Functions

Assume $D \subseteq \mathbb{F}_p$ for prime p. Then the following class is 1-universal:

$$\mathcal{H}_{p,m}^{\mathsf{lin}} := \{ x \mapsto ((a \times x) \oplus b) \bmod m \mid a \in \mathbb{F}_p^*, b \in \mathbb{F}_p \}.$$

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Let $x \neq y \in \mathbb{F}_p$. (To show: $\Pr_{h \sim \mathcal{H}_{p,m}^{\text{lin}}}[h(x) = h(y)] \le 1/m$.)

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Let $x \neq y \in \mathbb{F}_p$. (To show: $\Pr_{h \sim \mathcal{H}_{p,m}^{\text{lin}}}[h(x) = h(y)] \leq 1/m$.)

Define
$$c = (a \times x) \oplus b$$

 $d = (a \times y) \oplus b$

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$$c = (a \times x) \oplus b$$
 $\Leftrightarrow \begin{pmatrix} c \\ d \end{pmatrix} = \underbrace{\begin{pmatrix} x & 1 \\ y & 1 \end{pmatrix}}_{\text{regular!}} \begin{pmatrix} a \\ b \end{pmatrix}$.

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining 00000000

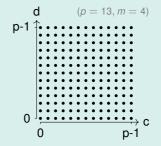
Use Case 2: Linear Probing

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Conceptions: What is a Hash Function?

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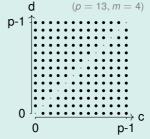
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$$P := \mathbb{F}_p imes \mathbb{F}_p \setminus \{(b,b) \mid b \in \mathbb{F}_p\}$$

Conceptions: What is a Hash Function?

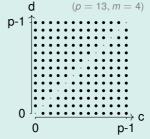
Use Case 1: Hash Table with Chaining ○○○○●○○ Use Case 2: Linear Probing

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Use Case 1: Hash Table with Chaining 00000000

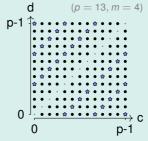
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$$P := \mathbb{F}_p \times \mathbb{F}_p \setminus \{(b,b) \mid b \in \mathbb{F}_p\}$$

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining ○○○○●○○ Use Case 2: Linear Probing

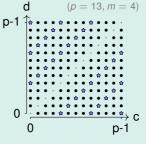
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$$=\Pr_{a,b}[c \bmod m=d \bmod m]=\Pr_{a,b}[(c,d)\in B]=\Pr_{c,d\sim\mathcal{U}(P)}[(c,d)\in B]$$

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$$\begin{aligned} & \operatorname{Pr}_{a,b \sim \mathcal{U}(\mathbb{F}_p^* \times \mathbb{F}_p)}[h(x) = h(y)] = \Pr_{a,b}[((a \times x) \oplus b) \bmod m = ((a \times y) \oplus b) \bmod m] \\ & = \Pr_{a,b}[c \bmod m = d \bmod m] = \Pr_{a,b}[(c,d) \in B] = \Pr_{c,d \sim \mathcal{U}(P)}[(c,d) \in B] = \frac{|B|}{|P|} \end{aligned}$$

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- The mapping $(a, b) \mapsto (c, d)$ is a bijection (for every $x \neq y$) from $\mathbb{F}_p^* \times \mathbb{F}_p \to P$.
- Define bad set $B := \{(c, d) \in P \mid c \mod m = d \mod m\}$. \hookrightarrow from picture: $\frac{|B|}{|P|} \le \frac{1}{m}$.

$$P := \mathbb{F}_p \times \mathbb{F}_p \setminus \{(b,b) \mid b \in \mathbb{F}_p\}$$

$$\Pr_{a,b\sim\mathcal{U}(\mathbb{F}_{p}^{*}\times\mathbb{F}_{p})}[h(x)=h(y)]=\Pr_{a,b}[((a\times x)\oplus b) \bmod m=((a\times y)\oplus b) \bmod m]$$

$$=\Pr_{a,b}[c \bmod m=d \bmod m]=\Pr_{a,b}[(c,d)\in B]=\Pr_{c,d\sim\mathcal{U}(P)}[(c,d)\in B]=\frac{|B|}{|P|}\leq \frac{1}{m}.\quad \Box$$

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining ○○○○●○○

Use Case 2: Linear Probing

Conclusion 000

Analysis of Hash Table with Chaining

... using a Universal Hash Family



Theorem

If $\mathcal{H} \subseteq [m]^D$ is a c-universal hash family then $T_{\mathrm{chaining}}(n, m, \mathcal{H}) \leq 2 + c\alpha = \mathcal{O}(1)$ if $\alpha \in \mathcal{O}(1)$ and $c \in \mathcal{O}(1)$.

Proof: Mostly the same.

$$\forall S \subseteq [D], \forall x \in D$$
:

$$\mathbb{E}_{h \sim \mathcal{U}(\mathcal{H})} \Big[1 + |\{y \in S \mid h(y) = h(x)\}| \Big]$$

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

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$$= \dots = 2 + \sum_{y \in S \setminus \{x\}} \Pr_{h \sim \mathcal{U}(\mathcal{H})} [h(y) = h(x)]$$

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining 00000000

Use Case 2: Linear Probing

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Analysis of Hash Table with Chaining

... using a Universal Hash Family



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$$= \ldots = 2 + \sum_{y \in S \setminus \{x\}} \Pr_{h \sim \mathcal{U}(\mathcal{H})} [h(y) = h(x)]$$

$$= 2 + \sum_{y \in S \setminus \{x\}} \frac{c}{m} \le 2 + \frac{cn}{m} = 2 + c\alpha. \quad \Box$$

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing

Conclusion

More Universal Families



Examples for Universal Hash Families

• " $((ax + b) \mod p) \mod m$ " is 1-universal

as discussed:
$$D = \mathbb{F}_p$$
, $R = [m]$,

$$\mathcal{H}_{p,m}^{\mathsf{lin}} := \{x \mapsto ((a \times b) \oplus b) \bmod m \mid a \in \mathbb{F}_p^*, b \in \mathbb{F}_p\}$$

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More Universal Families



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(ax mod p) mod m" is only 2-universal:

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More Universal Families



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Multiply-Shift is 2-universal:

$$D = \{0, \dots, 2^{w} - 1\}, \qquad R = \{0, \dots, 2^{\ell} - 1\}$$

$$\mathcal{H} = \{x \mapsto \lfloor ((a \cdot x + b) \bmod 2^{w})/2^{w - \ell} \rfloor \mid$$

$$odd \ a \in \{1, \dots, 2^{w} - 1\}, b \in \{0, \dots, 2^{w} - 1\}.\}$$

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining 0000000

Use Case 2: Linear Probing

Conclusion

More Universal Families



Examples for Universal Hash Families

• " $((ax + b) \mod p) \mod m$ " is 1-universal

as discussed:
$$D = \mathbb{F}_{\rho}$$
, $R = [m]$, $\mathcal{H}_{\rho,m}^{\text{lin}} := \{x \mapsto ((a \times b) \oplus b) \text{ mod } m \mid a \in \mathbb{F}_{\rho}^*, b \in \mathbb{F}_{\rho}\}$

■ "(ax mod p) mod m" is only 2-universal:

$$D = \mathbb{F}_p, \qquad R = [m],$$

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Selling point of multiply shift:

- "x mod 2"" drops some higher order bits
- " $\lfloor x/2^{w-\ell} \rfloor$ drops some lower order bits
- No division or modulo operation needed!

For w = 32 (taken from Thorup 2015):

```
uint32_t hash(uint32_t x, uint32_t l, uint64_t a) {
    return (a * x + b) >> (64-l);
}
```

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining ○○○○○○●

Use Case 2: Linear Probing

Conclusion 000

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- - Hashing in the Wild
 - What should a Theorist do?
- - Using SUHA
 - Using Universal Hashing
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 - Using SUHA
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Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining 00000000

Use Case 2: Linear Probing 000000000000000

Conclusion 000



S : set of n keys m: # of buckets $\alpha = n/m$



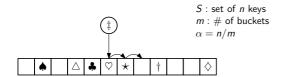
Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining 00000000

Use Case 2: Linear Probing 000000000000000

Conclusion 000





Operations

For key x probe buckets $h(x),h(x)+1,h(x)+2,\ldots\pmod{m}$. Insert. Put x into first empty bucket.



S: set of n keys m: # of buckets $\alpha = n/m$



Operations

For key *x probe* buckets $h(x),h(x)+1,h(x)+2,... \pmod{m}$. Insert. Put x into first empty bucket.

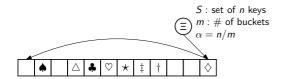
Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining 00000000

Use Case 2: Linear Probing 000000000000000

Conclusion





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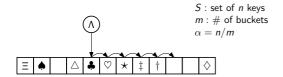
Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing

Conclusion

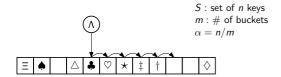




Operations

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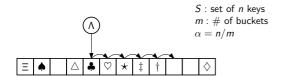
Operations

For key x probe buckets $h(x),h(x)+1,h(x)+2,\ldots\pmod{m}$.

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Lookup. Look for x, abort when encountering empty bucket.





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Delete. Lookup and remove x and \triangle check if a key to the

right wants to move into the hole.

 \hookrightarrow For details see https://en.wikipedia.org/wiki/Linear_probing

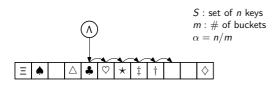
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Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing

Conclusion 000





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Running Times

Lookup($x \in S$): At most x's insertion time.

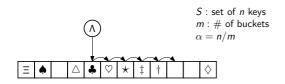
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Running Times

- Lookup($x \in S$): At most x's insertion time.
- Lookup($x \notin S$): At most the time it would take to insert x now.

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

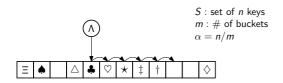
Use Case 2: Linear Probing

Conclusion

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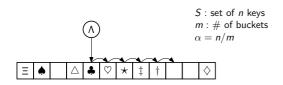
Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing ••••••••••••••

Conclusion





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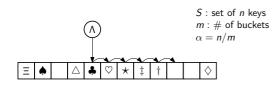
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Theorem: Linear Probing under SUHA

Let $T_{n,m}$ be the random insertion time into a linear probing hash table. If $\frac{1}{2} \le \alpha = \frac{n}{m} < \alpha_{\text{max}}$ for some $\alpha_{\rm max} <$ 1 then under SUHA we have

$$\mathbb{E}[T_{n,m}] =$$

$$\mathcal{O}(1)$$
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Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

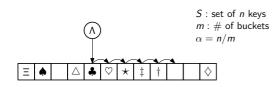
Use Case 2: Linear Probing

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$$\mathbb{E}[T_{n,m}] = \mathcal{O}(\frac{1}{(1-\alpha_{\max})^2}) = \mathcal{O}(1)$$
. (not here)

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

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- - Hashing in the Wild
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Chernoff

For $X \sim Bin(n, p)$ and $\varepsilon \in [0, 1]$ we have $\Pr[X \geq (1 + \varepsilon)\mathbb{E}[X]] \leq \exp(-\varepsilon^2 \mathbb{E}[X]/3)$.



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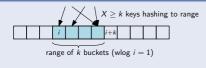
Lemma: $Pr[\ge k \text{ hits in segment of length } k]$ X > k keys hashing to range range of k buckets (wlog i = 1) Let $k \in \mathbb{N}$ and $X = |\{y \in S \mid h(y) \in \{1, ..., k\}\}|$. Then $\Pr_{h \sim \mathcal{U}(R^D)}[X \ge k] \le \exp(-(1-\alpha)^2 k/3).$



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Lemma: $Pr[\geq k \text{ hits in segment of length } k]$



Let
$$k \in \mathbb{N}$$
 and $X = |\{y \in S \mid h(y) \in \{1, ..., k\}\}|$.

Then
$$\Pr_{h \sim \mathcal{U}(B^{\mathsf{D}})}[X \geq k] \leq \exp(-(1-\alpha)^2 k/3).$$

Proof

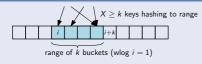
Let
$$S = \{x_1, \dots, x_n\}$$
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Then $X = \sum_{i \in [n]} X_i \sim Bin(n, \frac{k}{m})$ with $\mathbb{E}[X] = \frac{kn}{m} = \alpha k$.



Chernoff

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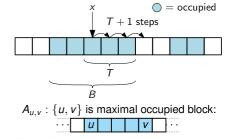
$$\Pr[X \ge k] = \Pr[X \ge \frac{1}{\alpha} \mathbb{E}[X]]$$

$$= \Pr[X \ge (1 + \frac{1 - \alpha}{\alpha}) \mathbb{E}[X]]$$

$$\le \exp(-(\frac{1 - \alpha}{\alpha})^2 \alpha k / 3)$$

$$\le \exp(-(1 - \alpha)^2 k / 3). \text{ (using } \frac{1}{2} \le \alpha \le 1)$$

 $\mathbb{E}[T]$



Reasoning:

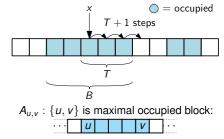
Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining 00000000

Use Case 2: Linear Probing 0000000000000000

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 $\mathbb{E}[T] \leq \mathbb{E}[B]$



Reasoning:

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining 00000000

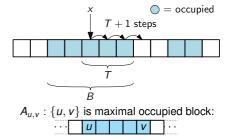
Use Case 2: Linear Probing 0000000000000000

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References

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$$\mathbb{E}[T] \leq \mathbb{E}[B] = \sum_{k \geq 1} k \cdot \Pr[B = k]$$



Reasoning:

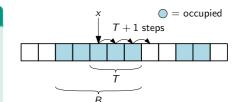
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Use Case 2: Linear Probing 0000000000000000

Conclusion

$$\mathbb{E}[T] \leq \mathbb{E}[B] = \sum_{k \geq 1} k \cdot \Pr[B = k] = \sum_{k \geq 1} k \cdot \Pr\left[\bigcup_{d=0}^{k-1} A_{h(x)-d,h(x)-d+k-1}\right]$$



 $A_{u,v}: \{u,v\}$ is maximal occupied block:

Reasoning:

Conceptions: What is a Hash Function?

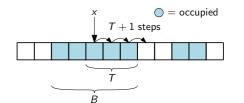
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$$\stackrel{(1)}{\leq} \sum_{k \geq 1} k \cdot \sum_{d=0}^{k-1} \Pr\left[A_{h(x)-d,h(x)-d+k-1}\right]$$



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Reasoning:

(1) Union Bound.

Conceptions: What is a Hash Function?

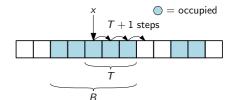
Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing 0000000000000000

Conclusion

$$\mathbb{E}[T] \leq \mathbb{E}[B] = \sum_{k \geq 1} k \cdot \Pr[B = k] = \sum_{k \geq 1} k \cdot \Pr\left[\bigcup_{d=0}^{k-1} A_{h(x)-d,h(x)-d+k-1}\right]$$

$$\overset{(1)}{\leq} \sum_{k \geq 1} k \cdot \sum_{d=0}^{k-1} \Pr \left[A_{h(x)-d,h(x)-d+k-1} \right] \overset{(2)}{=} \sum_{k \geq 1} k \cdot k \cdot \Pr[A_{1,k}]$$



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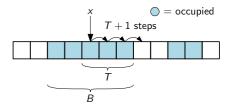
Reasoning:

- (1) Union Bound.
- (2) h(x) is independent of keys in the table and hash distribution is invariant under cyclic shifts.

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$$\stackrel{\text{(3)}}{\leq} \sum_{k \geq 1} k^2 \cdot \Pr[|\{y \in S \mid h(y) \in \{1, \dots, k\}| \geq k]$$



 $A_{u,v}: \{u,v\}$ is maximal occupied block: $\dots |u| |v| |v|$

Reasoning:

- (1) Union Bound.
- (2) h(x) is independent of keys in the table and hash distribution is invariant under cyclic shifts.
- (3) Note: Keys stored in block cannot come in from the left.

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing

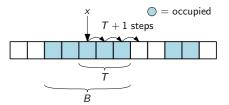
Conclusion 000

$$\mathbb{E}[T] \leq \mathbb{E}[B] = \sum_{k \geq 1} k \cdot \Pr[B = k] = \sum_{k \geq 1} k \cdot \Pr\left[\bigcup_{d=0}^{k-1} A_{h(x)-d,h(x)-d+k-1}\right]$$

$$\stackrel{(1)}{\leq} \sum_{k\geq 1} k \cdot \sum_{d=0}^{k-1} \Pr\left[A_{h(x)-d,h(x)-d+k-1}\right] \stackrel{(2)}{=} \sum_{k\geq 1} k \cdot k \cdot \Pr[A_{1,k}]$$

$$\overset{(3)}{\leq} \sum_{i \in \mathcal{I}} k^2 \cdot \Pr[|\{y \in \mathcal{S} \mid h(y) \in \{1, \dots, k\}| \geq k]$$

$$\stackrel{(4)}{\leq} \sum_{k \geq 1} k^2 \cdot \exp(-(1-\alpha)^2 k/3)$$



 $A_{u,v}: \{u,v\}$ is maximal occupied block:

Reasoning:

- (1) Union Bound.
- (2) h(x) is independent of keys in the table and hash distribution is invariant under cyclic shifts.
- (3) Note: Keys stored in block cannot come in from the left.
- (4) Chernoff argument from previous slide.

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

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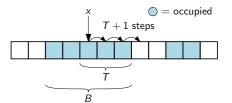
$$\mathbb{E}[T] \leq \mathbb{E}[B] = \sum_{k \geq 1} k \cdot \Pr[B = k] = \sum_{k \geq 1} k \cdot \Pr\left[\bigcup_{d=0}^{k-1} A_{h(x)-d,h(x)-d+k-1}\right]$$

$$\stackrel{(1)}{\leq} \sum_{k\geq 1} k \cdot \sum_{d=0}^{k-1} \Pr\left[A_{h(x)-d,h(x)-d+k-1}\right] \stackrel{(2)}{=} \sum_{k\geq 1} k \cdot k \cdot \Pr[A_{1,k}]$$

$$\overset{(3)}{\leq} \sum_{k \geq 1} k^2 \cdot \Pr[|\{y \in S \mid h(y) \in \{1, \dots, k\}| \geq k]]$$

$$\stackrel{\text{(4)}}{\leq} \sum_{k>1} k^2 \cdot \exp(-(1-\alpha)^2 k/3)$$

$$\leq \sum_{k\geq 1} k^2 \cdot \exp(-(1-\alpha_{\max})^2 k/3)$$



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$$\mathbb{E}[T] \leq \mathbb{E}[B] = \sum_{k \geq 1} k \cdot \Pr[B = k] = \sum_{k \geq 1} k \cdot \Pr\left[\bigcup_{d=0}^{k-1} A_{h(x)-d,h(x)-d+k-1}\right]$$

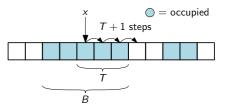
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$$\stackrel{\text{(4)}}{\leq} \sum_{k \geq 1} k^2 \cdot \exp(-(1 - \alpha)^2 k/3)$$

$$\leq \sum_{k \geq 1} k^2 \cdot \exp(-(1 - \alpha_{\text{max}})^2 k/3) = \mathcal{O}(1).$$

Wolfram Alpha gives:
$$\int_0^\infty k^2 \exp(-(1-\alpha_{\max})^2 k/3) = \frac{54}{(1-\alpha_{\max})^6}.$$



 $A_{u,v}: \{u,v\}$ is maximal occupied block:

Reasoning:

- (1) Union Bound.
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Conceptions: What is a Hash Function?

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 - Using SUHA
 - Using Universal Hashing
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Degrees of Independence



(Mutual / Collective) Independence

A family \mathcal{E} of **events** is **independent** if $\forall k \in \mathbb{N}$ and distinct $E_1, \dots, E_k \in \mathcal{E}$ we have

$$\Pr\left[\bigcap_{i=1}^k E_i\right] = \prod_{i=1}^k \Pr[E_i].$$

A family \mathcal{X} of discrete **random variables** is **independent** if $\forall k \in \mathbb{N}$, distinct $X_1, \dots, X_k \in \mathcal{X}$ and all $x_1, \dots, x_k \in \mathbb{R}$ we have

$$\Pr\left[\bigwedge_{i=1}^k X_i = x_i\right] = \prod_{i=1}^k \Pr[X_i = x_i].$$

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Degrees of Independence



Pairwise Independence

A family \mathcal{E} of **events** is **pairwise independent** if for distinct $E_1, E_2 \in \mathcal{E}$ we have

$$\Pr\left[E_1 \cap E_2\right] = \Pr[E_1] \cdot \Pr[E_2].$$

A family \mathcal{X} of discrete **random variables** is **pairwise independent** if for all distinct $X_1, X_2 \in \mathcal{X}$ and all $x_1, x_2 \in \mathbb{R}$ we have

$$\Pr\left[X_1 = x_1 \land X_2 = x_2\right] = \Pr[X_1 = x_1] \cdot \Pr[X_2 = x_2].$$

Degrees of Independence



d-wise Independence

A family \mathcal{E} of events is *d*-wise independent if $\forall k \in \{2, ..., d\}$ and distinct $E_1, ..., E_k \in \mathcal{E}$ we have

$$\Pr\left[\bigcap_{i=1}^k E_i\right] = \prod_{i=1}^k \Pr[E_i].$$

A family \mathcal{X} of discrete **random variables** is *d*-wise independent if $\forall k \in \{2, ..., d\}$, distinct $X_1, ..., X_k \in \mathcal{X}$ and all $x_1, ..., x_k \in \mathbb{R}$ we have

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Definition: d-Independent Hash Family

A family $\mathcal{H} \subseteq [R]^D$ of hash functions is *d-independent* if for distinct $x_1, \ldots, x_d \in D$ and any $i_1, \ldots, i_d \in R$: (grey is implied by black)

$$\Pr_{h \sim \mathcal{U}(\mathcal{H})}[h(x_1) = i_1 \wedge \ldots \wedge h(x_d) = i_d] = \prod_{j=1}^d \Pr_{h \sim \mathcal{U}(\mathcal{H})}[h(x_j) = i_j] = |R|^{-d}.$$



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Alternative Definition

 \mathcal{H} is *d*-independent if for $h \sim \mathcal{U}(\mathcal{H})$

- the family $(h(x))_{x \in D}$ of random variables is *d*-independent *and*
- $h(x) \sim \mathcal{U}(R)$ for each $x \in D$.



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Theorem

Let $D = R = \mathbb{F}$ be a finite field. Then

$$\mathcal{H} := \{x \mapsto \sum_{i=0}^{d-1} a_i x^i \mid a_0, \dots, a_{d-1} \in \mathbb{F}\}$$

is a *d*-independent family.

Note: $\mathcal{H} \subseteq \mathbb{F}^{\mathbb{F}} \leadsto$ not yet useful.

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

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References



Definition: d-Independent Hash Family

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Note: $\mathcal{H} \subseteq \mathbb{F}^{\mathbb{F}} \leadsto$ not yet useful.

Corollary: Smaller Ranges (proof omitted)

- If m divides $|\mathbb{F}|$, then adding "mod m" gives a *d*-independent family $\mathcal{H}' \subseteq [m]^{\mathbb{F}}$.
- If m does not divide $|\mathbb{F}|$, then adding "mod m" gives a family $\mathcal{H}' \subseteq [m]^{\mathbb{F}}$ such that for $h \sim \mathcal{U}(\mathcal{H}')$ the family $(h(x))_{x\in\mathbb{F}}$ is *d*-independent but only *approximately* uniformly distributed in [m].

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Proof: $\mathcal{H}:=\{x\mapsto \sum_{i=0}^{d-1}a_ix^i\mid a_0,\ldots,a_{d-1}\in\mathbb{F}\}$ is d-independent

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

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Use Case 2: Linear Probing

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References

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Let $x_1, \ldots, x_d \in \mathbb{F}$ be distinct keys and $i_1, \ldots i_d \in \mathbb{F}$ arbitrary.

$$\hookrightarrow$$
 to show : $\Pr_{h \sim \mathcal{U}(\mathcal{H})}[\forall j \in [d] : h(x_j) = i_j] = |\mathbb{F}|^{-d}$.

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

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Conclusion

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For $h \in \mathcal{H}$ (given via a_0, \dots, a_{d-1}) the following is equivalent:

$$h(x_{1}) = i_{1} \qquad a_{0} + a_{1}x_{1} + \dots + a_{d-1}x_{1}^{d-1} = i_{1}$$

$$h(x_{2}) = i_{2} \qquad a_{0} + a_{1}x_{2} + \dots + a_{d-1}x_{2}^{d-1} = i_{2}$$

$$\vdots \qquad \vdots$$

$$h(x_{d}) = i_{d} \qquad a_{0} + a_{1}x_{d} + \dots + a_{d-1}x_{d}^{d-1} = i_{d}$$

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

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$$h(x_{1}) = i_{1} \qquad a_{0} + a_{1}x_{1} + \dots + a_{d-1}x_{1}^{d-1} = i_{1} h(x_{2}) = i_{2} \qquad a_{0} + a_{1}x_{2} + \dots + a_{d-1}x_{2}^{d-1} = i_{2} \vdots \qquad \vdots \qquad \vdots h(x_{d}) = i_{d} \qquad a_{0} + a_{1}x_{d} + \dots + a_{d-1}x_{d}^{d-1} = i_{d} \qquad \underbrace{\begin{pmatrix} 1 & x_{1} & x_{1}^{2} & \dots & x_{1}^{d-1} \\ 1 & x_{2} & x_{2}^{2} & \dots & x_{2}^{d-1} \\ \vdots & & \ddots & \vdots \\ 1 & x_{d} & x_{d}^{2} & \dots & x_{d}^{d-1} \end{pmatrix}}_{1} \cdot \begin{pmatrix} a_{0} \\ a_{1} \\ \vdots \\ a_{d-1} \end{pmatrix} = \begin{pmatrix} i_{1} \\ i_{2} \\ \vdots \\ i_{d} \end{pmatrix}$$

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$$\vdots \qquad \vdots \qquad \vdots \qquad \vdots \qquad \vdots \qquad \vdots \qquad \vdots$$

$$h(x_{d}) = i_{d} \qquad a_{0} + a_{1}x_{d} + \dots + a_{d-1}x_{d}^{d-1} = i_{d} \qquad \underbrace{ \left(\begin{array}{cccc} 1 & x_{1} & x_{1}^{2} & \dots & x_{1}^{d-1} \\ 1 & x_{2} & x_{2}^{2} & \dots & x_{2}^{d-1} \\ \vdots & & \ddots & \vdots \\ 1 & x_{d} & x_{d}^{2} & \dots & x_{d}^{d-1} \end{array} \right) }_{\text{Vandermonde matrix } M \Rightarrow \text{regular}}$$

$$\bullet \left(\begin{array}{c} a_{0} \\ a_{1} \\ \vdots \\ a_{d-1} \end{array} \right) = \left(\begin{array}{c} i_{1} \\ i_{2} \\ \vdots \\ i_{d} \end{array} \right)$$

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Use Case 1: Hash Table with Chaining

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Proof: $\mathcal{H} := \{x \mapsto \sum_{i=0}^{d-1} a_i x^i \mid a_0, \dots, a_{d-1} \in \mathbb{F}\}$ is *d*-independent

Let $x_1, \ldots, x_d \in \mathbb{F}$ be distinct keys and $i_1, \ldots, i_d \in \mathbb{F}$ arbitrary.

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$$\Leftrightarrow \underbrace{\begin{pmatrix} 1 & x_{1} & x_{1}^{2} & \dots & x_{1}^{d-1} \\ 1 & x_{2} & x_{2}^{2} & \dots & x_{d}^{d-1} \\ \vdots & & & \ddots & \vdots \\ 1 & x_{d} & x_{d}^{2} & \dots & x_{d}^{d-1} \end{pmatrix}}_{\text{Vandermonde matrix } M \Rightarrow \text{ regular}} \cdot \begin{pmatrix} a_{0} \\ a_{1} \\ \vdots \\ a_{d-1} \end{pmatrix} = \begin{pmatrix} i_{1} \\ i_{2} \\ \vdots \\ i_{d} \end{pmatrix}$$

Exactly one vector $\vec{a} = M^{-1} \cdot \vec{i}$ solves the equation.

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

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For $h \in \mathcal{H}$ (given via a_0, \ldots, a_{d-1}) the following is equivalent:

Exactly one vector $\vec{a} = M^{-1} \cdot \vec{i}$ solves the equation.

$$\Rightarrow \Pr\nolimits_{h \sim \mathcal{U}(\mathcal{H})}[\forall j : h(x_j) = i_j] = \Pr\nolimits_{a_0, \dots, a_{d-1} \sim \mathcal{U}(\mathbb{F})}[\vec{a} = M^{-1} \cdot \vec{i}\,] = \mathbb{F}^{-d}. \quad \Box$$

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Use Case 1: Hash Table with Chaining

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Concentration Bound for *d***-Independent Variables**



(Tricky) Exercise

Let d be even and $X_1, \ldots, X_n \sim Ber(p)$ a d-independent family of random variables with $p = \Omega(1/n)$. Let $X = \sum_{i=1}^n X_i$. Then for any $\varepsilon > 0$ we have

$$\Pr[X - \mathbb{E}[X] \ge \varepsilon \mathbb{E}[X]] = \mathcal{O}(\varepsilon^{-d} \mathbb{E}[X]^{-d/2}).$$

Concentration Bound for d-Independent Variables



Tricky) Exercise

Let d be even and $X_1, \ldots, X_n \sim Ber(p)$ a d-independent family of random variables with $p = \Omega(1/n)$. Let $X = \sum_{i=1}^{n} X_i$. Then for any $\varepsilon > 0$ we have

$$\Pr[X - \mathbb{E}[X] \ge \varepsilon \mathbb{E}[X]] = \mathcal{O}(\varepsilon^{-d} \mathbb{E}[X]^{-d/2}).$$

Remark: Weaker than Chernoff, stronger than Chebyshev

Chebycheff gives $\Pr[X - \mathbb{E}[X] \ge \varepsilon \mathbb{E}[X]] \le \frac{1-p}{\varepsilon^2 \mathbb{E}[X]}$. (requires d = 2)

Chernoff gave $\Pr[X - \mathbb{E}[X] \ge \varepsilon \mathbb{E}[X]] \le \exp(-\varepsilon^2 \mathbb{E}[X]/3)$. (requires d = n).

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Use Case 1: Hash Table with Chaining

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Conclusion

again for d-independence



Lemma (last slide)

For *d*-independent $X_1,\ldots,X_n\sim Ber(p)$ and $X=\sum_{i\in[n]}X_i$ we have $\Pr[X\geq (1+\varepsilon)\mathbb{E}[X]]=\mathcal{O}(\varepsilon^{-d}\mathbb{E}[X]^{-d/2}).$

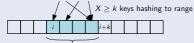
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Lemma: $\geq k$ hits in segment of length k



range of k buckets (wlog i = 1)

Let \mathcal{H} be a *d*-independent hash family and $h \sim \mathcal{U}(\mathcal{H})$. Let $k \in \mathbb{N}$ and $X = |\{y \in S \mid h(y) \in \{1, ..., k\}\}|$.

Then
$$\Pr[X \ge k] \le \mathcal{O}((1 - \alpha)^{-d} k^{-d/2}).$$

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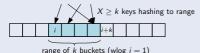
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Then
$$\Pr[X > k] < \mathcal{O}((1 - \alpha)^{-d} k^{-d/2}).$$

Proof

Let
$$S = \{x_1, \dots, x_n\}$$
 and $X_i = \mathbbm{1}_{\{h(x_i) \in \{1, \dots, k\}\}} \sim Ber(\frac{k}{m})$.
Then $X = \sum_{i \in [n]} X_i$ fits the Lemma with $\mathbb{E}[X] = \frac{kn}{m} = \alpha k$.

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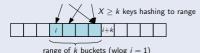
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Lemma: $\geq k$ hits in segment of length k



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$$\Pr[X \ge k] = \Pr[X \ge \frac{1}{\alpha} \mathbb{E}[X]]$$

$$= \Pr[X \ge (1 + \frac{1 - \alpha}{\alpha}) \mathbb{E}[X]]$$

$$= \mathcal{O}(\left(\frac{1 - \alpha}{\alpha}\right)^{-d} (\alpha k)^{-d/2})$$

$$\le \mathcal{O}((1 - \alpha)^{-d} k^{-d/2}). \text{ (using } \alpha \le 1)$$

Conceptions: What is a Hash Function?

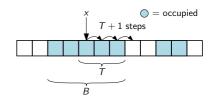
Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing ○○○○○○○○○○○○○

Conclusion 000

Under the same conditions as before, except with 9-independent hash functions, the insertion time $T_{n,m}$ for linear probing satisfies:

$$\mathbb{E}[T_{n,m}] = \mathcal{O}(1)$$



 $A_{u,v}: \{u,v\}$ is a maximal occupied block:

Reasoning:

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing 0000000000000000

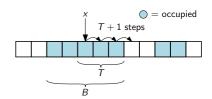
Conclusion

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Proof Sketch

 $\mathbb{E}[T]$



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Reasoning:

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing 0000000000000000

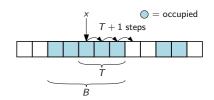
Conclusion

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$$\mathbb{E}[T_{n,m}] = \mathcal{O}(1)$$

Proof Sketch

$$\mathbb{E}[T] \leq \mathbb{E}[B]$$



 $A_{u,v}: \{u,v\}$ is a maximal occupied block:

Reasoning:

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing 0000000000000000

Conclusion

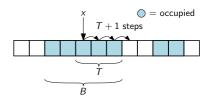
Under the same conditions as before, except with 9-independent hash functions, the insertion time $T_{n,m}$ for linear probing satisfies:

$$\mathbb{E}[T_{n,m}] = \mathcal{O}(1)$$

Proof Sketch

$$\mathbb{E}[T] \le \mathbb{E}[B] \le \dots$$

$$\stackrel{(1)}{\le} \sum_{k \ge 1} k^2 \cdot \Pr[|\{y \in S \mid h(y) \in \{1, \dots, k\}\}| \ge k]$$



 $A_{u,v}: \{u,v\}$ is a maximal occupied block: $\dots \quad u \quad v \quad \dots$

Reasoning:

 Same as before, except we have to condition on h(x) and may only use 8-independence in the following. (this is the hand wavy part!)

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing

Conclusion

Under the same conditions as before, except with 9-independent hash functions, the insertion time $T_{n,m}$ for linear probing satisfies:

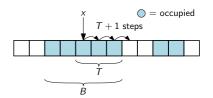
$$\mathbb{E}[T_{n,m}] = \mathcal{O}(1)$$

Proof Sketch

$$\mathbb{E}[T] \leq \mathbb{E}[B] \leq \dots$$

$$\leq \sum_{k \geq 1} k^2 \cdot \Pr[|\{y \in S \mid h(y) \in \{1, \dots, k\}\}| \geq k]$$

$$\leq \sum_{k \geq 1} k^2 \cdot \mathcal{O}((1 - \alpha)^{-8} k^{-8/2})$$



 $A_{u,v}: \{u,v\}$ is a maximal occupied block:

Reasoning:

- (1) Same as before, except we have to condition on h(x) and may only use 8-independence in the following. (this is the hand wavy part!)
- (2) Concentration bound from previous slide for d=8.

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing

Conclusion

Under the same conditions as before, except with 9-independent hash functions, the insertion time $T_{n,m}$ for linear probing satisfies:

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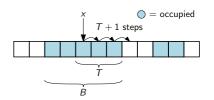
Proof Sketch

$$\mathbb{E}[T] \leq \mathbb{E}[B] \leq \dots$$

$$\stackrel{(1)}{\leq} \sum_{k \geq 1} k^2 \cdot \Pr[|\{y \in S \mid h(y) \in \{1, \dots, k\}\}| \geq k]$$

$$\stackrel{(2)}{\leq} \sum_{k \geq 1} k^2 \cdot \mathcal{O}((1 - \alpha)^{-8} k^{-8/2})$$

$$\leq \sum_{k \geq 1} k^{-2} \cdot \mathcal{O}((1 - \alpha)^{-8})$$



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Proof Sketch

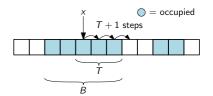
$$\mathbb{E}[T] \leq \mathbb{E}[B] \leq \dots$$

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$$\leq \sum_{k \geq 1} k^{-2} \cdot \mathcal{O}((1 - \alpha)^{-8})$$

 $\stackrel{\text{(3)}}{=} \frac{\pi^2}{6} \mathcal{O}((1-\alpha)^{-8}) = \mathcal{O}(1). \quad \Box$



 $A_{u,v}: \{u,v\}$ is a maximal occupied block:

Reasoning:

- (1) Same as before, except we have to condition on h(x) and may only use 8-independence in the following. (this is the hand wavy part!)
- (2) Concentration bound from previous slide for d=8.
- (3) If interested, see 3Blue1Brown video: https://www.youtube.com/watch?v=d-o3eB9sfls

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing

Conclusion

Final Remarks on Linear Probing + Universal Hashing



Much more is known about insertion times of linear probing:

- Any 5-independent family gives $\mathcal{O}(\frac{1}{(1-\alpha)^2})$. \hookrightarrow A. Pagh, R. Pagh, and Ruzic 2011
- An (artificially bad) 4-independent family gives $\Omega(\log n)$.
- A (well-designed) 4-independent family gives $\mathcal{O}(\frac{1}{(1-\alpha)^2})$.

Conclusion



Technical Takeaway: Performance of Hash Tables

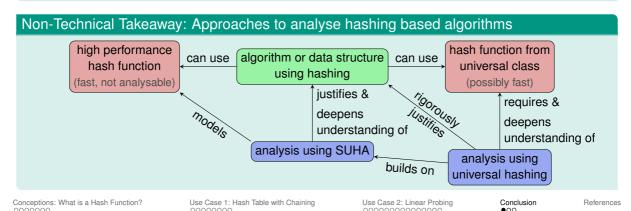
For both an ideal hash function (SUHA) and a random hash function from a suitable universal class, a hash table using **linear probing** or **chaining** provably has an expected running time of $\mathcal{O}(1)$ per operation.

Conclusion



Technical Takeaway: Performance of Hash Tables

For both an ideal hash function (SUHA) and a random hash function from a suitable universal class, a hash table using **linear probing** or **chaining** provably has an expected running time of $\mathcal{O}(1)$ per operation.

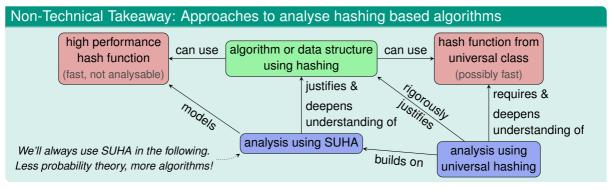


Conclusion



Technical Takeaway: Performance of Hash Tables

For both an **ideal hash function** (SUHA) and a random hash function from a suitable **universal class**, a hash table using **linear probing** or **chaining** provably has an expected running time of $\mathcal{O}(1)$ per operation.



Anhang: Mögliche Prüfungsfragen I



- Was könnte eine Idealvorstellung einer Hashfunktion sein? Inwiefern wäre eine ideale Hashfunktion nützlich? Was ist das Problem an dieser Vorstellung?
- Was ist die Simple Uniform Hashing Assumption (SUHA)? Was spricht dafür diese Annahme zu treffen? Welche Alternativen gibt es?
- Inwiefern ist eine pseudozufällige Funktion mit kryptographischen Ununterscheidbarkeitsgarantien nützlich für uns? Wie ist der Zusammenhang zur SUHA?*
- Universelles Hashing:
 - Wie ist c-Universalität definiert?
 - Welche c-universellen Hashklasse haben wir kennengelernt? Wie haben wir die c-Universalität bewiesen?
 - Wie ist d-Unabhängigkeit für eine Hashklasse definiert?
 - Welche d-universelle Hashklasse haben wir kennengelernt?
 - Welcher Zusammenhang besteht zwischen d-Unabhängigkeit und c-Universalität? (Übungsaufgabe)
 - Chernoff Schranken sind für Summen unabhängiger Zufallsvariablen gedacht. Was kann man machen, wenn die Zufallsvariablen nur d-unabhängig sind?*

Conceptions: What is a Hash Function?

Use Case 1: Hash Table with Chaining

Use Case 2: Linear Probing

Conclusion 000

Anhang: Mögliche Prüfungsfragen II



- Betrachten wir Hashing mit verketteten Listen:
 - Welche Schranke an die erwartete Einfügezeit haben wir bewiesen? Wie?
 - An welcher Stelle spielt die Verteilung der Hashfunktion eine Rolle?
 - Nenne eine hinreichende Eigenschaft, die eine universelle Hashklasse haben sollte, damit der Beweis funktioniert
- Betrachten wir Hashing mit linearem Sondieren:
 - Welche Schranke an die erwartete Laufzeit haben wir bewiesen? Wie?
 - An welcher Stelle spielt die Verteilung der Hashfunktion eine Rolle?
 - Nenne eine hinreichende Eigenschaft, die eine universelle Hashklasse haben sollte, damit der Beweis funktioniert
 - Wie wir diese Eigenschaft ausgenutzt?*



- [1] Anna Pagh, Rasmus Pagh, and Milan Ruzic. "Linear Probing with 5-wise Independence". In: *SIAM Rev.* 53.3 (2011), pp. 547–558. DOI: 10.1137/110827831. URL: https://doi.org/10.1137/110827831.
- [2] Mihai Pătraşcu and Mikkel Thorup. "On the *k*-Independence Required by Linear Probing and Minwise Independence". In: *ACM Trans. Algorithms* 12.1 (2016), 8:1–8:27. DOI: 10.1145/2716317. URL: https://doi.org/10.1145/2716317.
- [3] Mihai Puatracscu and Mikkel Thorup. "Twisted Tabulation Hashing". In: *Proceedings of the Twenty-Fourth Annual ACM-SIAM Symposium on Discrete Algorithms, SODA 2013, New Orleans, Louisiana, USA, January 6-8, 2013.* Ed. by Sanjeev Khanna. SIAM, 2013, pp. 209–228. DOI: 10.1137/1.9781611973105.16. URL: https://doi.org/10.1137/1.9781611973105.16.
- [4] Mikkel Thorup. "High Speed Hashing for Integers and Strings". In: CoRR abs/1504.06804 (2015). arXiv: 1504.06804. URL: http://arxiv.org/abs/1504.06804.