



Chapter 4 Amortized Analysis

Algorithm Theory WS 2018/19

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Amortized Analysis



What is the average cost of an operation in a worst case sequence of operations?

Amortized Cost

- Sequence of operations i = 1, 2, 3, ..., n
- Actual cost of op. i: t_i
- Amortized cost of op. i is a_i if for every possible seq. of op.,

$$T = \sum_{i=1}^{n} t_i \le \sum_{i=1}^{n} a_i$$

Example 2: Binary Counter



Incrementing a binary counter: determine the bit flip cost:

Operation	Counter Value	Cost
	00000	
1	00001	1
2	000 10	2
3	0001 <mark>1</mark>	1
4	00 100	3
5	0010 <mark>1</mark>	1
6	001 <mark>10</mark>	2
7	0011 <mark>1</mark>	1
8	0 1000	4
9	0100 <mark>1</mark>	1
10	010 <mark>10</mark>	2
11	0101 <mark>1</mark>	1
12	01 100	3
13	0110 <mark>1</mark>	1

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Observation:

Each increment flips exactly one <u>0</u> into a <u>1</u>

 $0010001111 \Longrightarrow 0010010000$

Idea:

- Have a bank account (with initial amount 0)
- Paying x to the bank account costs x
- Take "money" from account to pay for expensive operations

Applied to binary counter:

- Flip from 0 to 1: pay 1 to bank account (cost: 2)
- Flip from 1 to 0: take 1 from bank account (cost: 0)
- Amount on bank account = number of ones
 → We always have enough "money" to pay!

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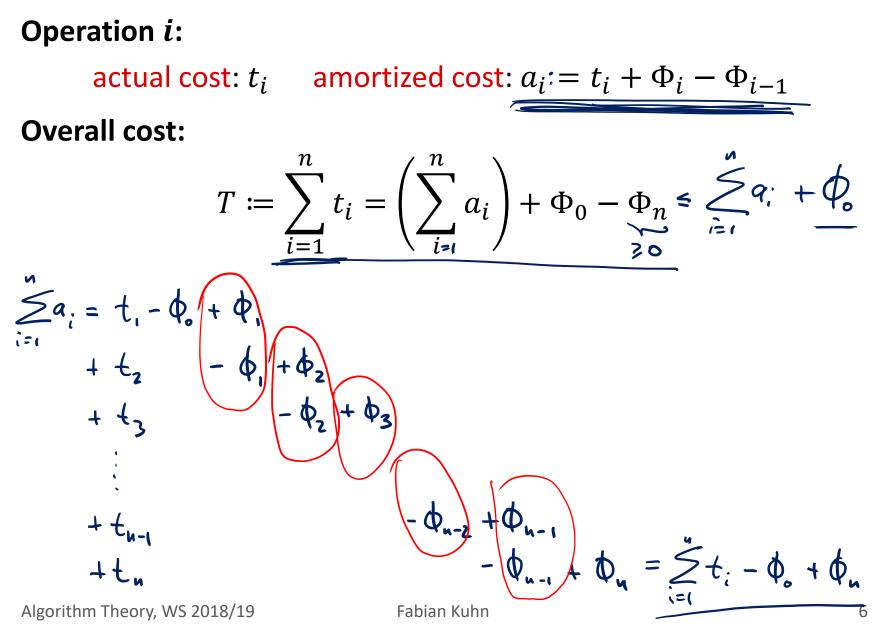
Potential Function Method

- Most generic and elegant way to do amortized analysis!
 - But, also more abstract than the others...
- State of data structure / system: $S \in S$ (state space) Potential function $\Phi: \mathcal{S} \to \mathbb{R}_{\geq 0}$
- **Operation** *i*:
 - t_i : actual cost of operation i
 - $\overline{S_i}$: state after execution of operation *i* (S_0 : initial state)
 - $\mathbf{\Phi}_i \coloneqq \Phi(S_i)$: potential after exec. of operation *i*
 - a_i : amortized cost of operation *i*:



Potential Function Method









• Potential function:

Φ: number of ones in current counter

- Clearly, $\Phi_0 = 0$ and $\Phi_i \ge 0$ for all $i \ge 0$
- Actual cost $\underline{t_i}$:
 - 1 flip from 0 to 1
 - $t_i 1$ flips from 1 to 0
- Potential difference: $\Phi_i \Phi_{i-1} = 1 (t_i 1) = 2 t_i$
- Amortized cost: $a_i = t_i + \Phi_i \Phi_{i-1} = 2$

Example 3: Dynamic Array



- How to create an array where the size dynamically adapts to the number of elements stored?
 - e.g., Java "ArrayList" or Python "list"

Implementation:

- Initialize with initial size N_0
- Assumptions: Array can only grow by appending new elements at the end
- If array is full, the size of the array is increased by a factor $\beta > 1$

Operations (array of size *N***):**

- read / write: actual cost O(1)
- <u>append</u>: actual cost is O(1) if array is not full, otherwise the append cost is $O(\beta \cdot N)$ (new array size)

ßN

Example 3: Dynamic Array

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Notation:

- *n*: number of elements stored
- N: current size of array

Cost $\underline{t_i}$ of i^{th} append operation: $t_i = \begin{cases} 1 & \text{if } n < N \\ \beta \cdot N & \text{if } n = N \end{cases}$

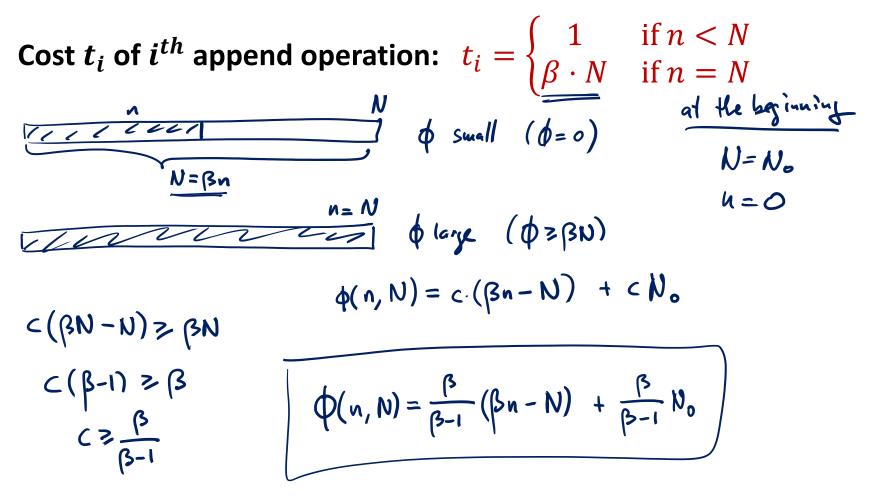
Claim: Amortized append cost is O(1)

Potential function Φ ?

- should allow to pay expensive append operations by cheap ones
- when array is full, Φ has to be large
- immediately after increasing the size of the array, Φ should be small again

Dynamic Array: Potential Function

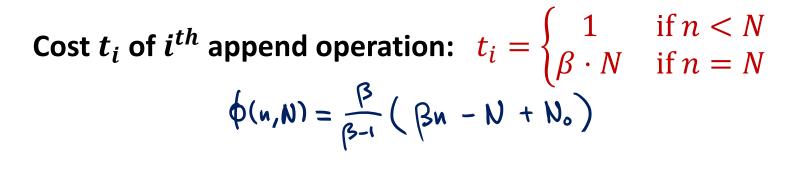




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Dynamic Array: Amortized Cost $a_{i}=\epsilon_{i}+\phi_{i}-\phi_{i-1}$





amorfized cost a; $(ase | (u < N)) \quad a_i = 1 + \frac{\beta^2}{\beta - 1}(n + 1 - n) = 1 + \frac{\beta^2}{\beta - 1}$ (ase 2 (n=N): $a_{i} = \beta \cdot N + \left[\frac{\beta}{\beta - 1}\left(\beta(N+1) - \beta N\right) - \frac{\beta}{\beta - 1}\left(\beta N - N\right)\right] = \frac{\beta^{2}}{\beta - 1}$ $\frac{\beta^2}{\beta^{-1}} - \frac{\beta}{\beta^{-1}} (\beta - 1) \cdot N$ (3N) $\frac{\text{amortized cost:}}{\beta - 1}$ $\frac{\beta^2}{\beta^{-1}}$ Algorithm Theory, WS 2018/19 Fabian Kuhn

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