Lecture 17 (Amortized Analysis)

CLRS 17-1, 17-2, 17-3, 17-4

University of Manitoba
Amortized vs Average Analysis

- Both are concerned with the cost averaged over a sequence of operations.
Amortized vs Average Analysis

- Both are concerned with the cost averaged over a sequence of operations.

- Average case analysis relies on probabilistic assumptions about the input or the data structure.
  - There is an underlying probability distribution.
  - The worst-case might be met with some small chance (you can be ‘lucky’ or not).
Amortized vs Average Analysis

- Both are concerned with the cost averaged over a sequence of operations.
- Average case analysis relies on probabilistic assumptions about the input or the data structure.
  - There is an underlying probability distribution.
  - The worst-case might be met with some small chance (you can be ‘lucky’ or not).
- Amortized analysis consider consider a sequence of consecutive operations.
  - Bound the total cost for \( m \) operations
  - This gives the amortized cost \( B(n) \) per operation
  - The amortized cost is only a function of \( n \), the size of stored data
  - Unlike average case analysis, there is no probability distribution
  - Every sequence of \( m \) operations is guaranteed to have worst-case time at most \( mB(n) \), regardless of the input or the sequence of operations (regardless of how lucky you are).
Amortized vs Average Analysis

- Let's compare two algorithms A and B.
- A performs operations which take $\Theta(n)$ time in the worst case and $\Theta(\log n)$ on average.
- B performs operations which take $\Theta(n)$ time in the worst case and amortized $\Theta(\log n)$.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>worst-case time per operation</th>
<th>average/amortized time per operation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithm A</td>
<td>$\Theta(n)$</td>
<td>$\Theta(\log n)$ average</td>
</tr>
<tr>
<td>Algorithm B</td>
<td>$\Theta(n)$</td>
<td>$\Theta(\log n)$ amortized</td>
</tr>
</tbody>
</table>
Let's compare two algorithms A and B:

- A performs operations which take $\Theta(n)$ time in the worst case and $\Theta(\log n)$ on average.
- B performs operations which take $\Theta(n)$ time in the worst case and amortized $\Theta(\log n)$.

<table>
<thead>
<tr>
<th></th>
<th>worst-case time per operation</th>
<th>average/amortized time per operation</th>
<th>worst-case time for $m$ operations</th>
<th>average time for $m$ operations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithm A</td>
<td>$\Theta(n)$</td>
<td>$\Theta(\log n)$ average</td>
<td>$\Theta(m \cdot n)$</td>
<td></td>
</tr>
<tr>
<td>Algorithm B</td>
<td>$\Theta(n)$</td>
<td>$\Theta(\log n)$ amortized</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Amortized vs Average Analysis

- Let’s compare two algorithms A and B
  - A performs operations which take $\Theta(n)$ time in the worst case and $\Theta(\log n)$ on average.
  - B performs operations which take $\Theta(n)$ time in the worst case and amortized $\Theta(\log n)$.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>worst-case time per operation</th>
<th>average/amortized time per operation</th>
<th>worst-case time for $m$ operations</th>
<th>average time for $m$ operations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithm A</td>
<td>$\Theta(n)$</td>
<td>$\Theta(\log n)$ average</td>
<td>$\Theta(m \cdot n)$</td>
<td></td>
</tr>
<tr>
<td>Algorithm B</td>
<td>$\Theta(n)$</td>
<td>$\Theta(\log n)$ amortized</td>
<td>$\Theta(m \log n)$</td>
<td></td>
</tr>
</tbody>
</table>
Let’s compare two algorithms A and B.

A performs operations which take $\Theta(n)$ time in the worst case and $\Theta(\log n)$ on average.

B performs operations which take $\Theta(n)$ time in the worst case and amortized $\Theta(\log n)$.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>worst-case time per operation</th>
<th>average/amortized time per operation</th>
<th>worst-case time for $m$ operations</th>
<th>average time for $m$ operations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithm A</td>
<td>$\Theta(n)$</td>
<td>$\Theta(\log n)$ average</td>
<td>$\Theta(m \cdot n)$</td>
<td>$\Theta(m \log n)$</td>
</tr>
<tr>
<td>Algorithm B</td>
<td>$\Theta(n)$</td>
<td>$\Theta(\log n)$ amortized</td>
<td>$\Theta(m \log n)$</td>
<td></td>
</tr>
</tbody>
</table>
Let’s compare two algorithms A and B

A performs operations which take $\Theta(n)$ time in the worst case and $\Theta(\log n)$ on average.

B performs operations which take $\Theta(n)$ time in the worst case and amortized $\Theta(\log n)$.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>worst-case time per operation</th>
<th>average/amortized time per operation</th>
<th>worst-case time for $m$ operations</th>
<th>average time for $m$ operations</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$\Theta(n)$</td>
<td>$\Theta(\log n)$ average</td>
<td>$\Theta(m \cdot n)$</td>
<td>$\Theta(m \log n)$</td>
</tr>
<tr>
<td>B</td>
<td>$\Theta(n)$</td>
<td>$\Theta(\log n)$ amortized</td>
<td>$\Theta(m \log n)$</td>
<td>$\Theta(m \log n)$</td>
</tr>
</tbody>
</table>
Bit Counter

- Start from an initial configuration where all bits are ‘0’
- Each operation increments the encoded number
- We want to know how many bits are flipped per operation
Bit Counter

- Start from an initial configuration where all bits are ‘0’
- Each operation increments the encoded number
- We want to know how many bits are flipped per operation
- The $i$’th bit from right is flipped iff all $i - 1$ bits on its right are 1 before the increment ($i \geq 0$)
  - After the flip all bits on the right will be 0.
  - In the next $2^i - 1$ operations after the flip the bit is not flipped.
  - The $i$’th bit is flipped once in $2^i$ operations
Bit Counter

- For a sequence of $m$ operations, the $i$'th bit is flipped $\frac{m}{2^i}$ times.
- Total number of flips will be at most

$$m + \frac{m}{2} + \ldots + \frac{m}{2^{[\log m]}} < m \sum_{i=0}^{\infty} \frac{1}{2^i} = 2m$$

The amortized number of flips per operation is $2 = \Theta(1)$ flips.

The worst case number of flips is $\Theta(\log m)$; but it never happens that a sequence of $m$ operations have $m \Theta(\log m)$ flips!
Bit Counter

- For a sequence of $m$ operations, the $i$’th bit is flipped $\frac{m}{2^i}$ times.
- Total number of flips will be at most

$$m \left( \frac{m}{2^0} \right) + \frac{m}{2} \left( \frac{m}{2^1} \right) + \ldots + \frac{m}{2^{\lceil \log m \rceil}} \left( \frac{m}{2^{\lceil \log m \rceil}} \right) < m \sum_{i=0}^{\infty} \frac{1}{2^i} = 2m$$

- The amortized number of flips per operation is $2 = \Theta(1)$ flips.
Bit Counter

- For a sequence of $m$ operations, the $i$'th bit is flipped $\frac{m}{2^i}$ times.
- Total number of flips will be at most

$$m + \frac{m}{2} + \ldots + \frac{m}{2^{\lceil \log m \rceil}} < m \sum_{i=0}^{\infty} \frac{1}{2^i} = 2m$$

- The amortized number of flips per operation is $2 = \Theta(1)$ flips.
- The worst case number of flips is $\Theta(\log m)$; but it never happens that a sequence of $m$ operations have $m\Theta(\log m)$ flips!

<table>
<thead>
<tr>
<th>Log $m$</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Initial configuration

After 1st increment: 1 bit flipped
After 2nd increment: 2 bits flipped
After 111th increment: 1 bit flipped
After 112th increment: 5 bits flipped
Amortized Analysis Review

- Considering a sequence of \( m \) operations for sufficiently large \( m \):
  - Some operations are more ‘expensive’ and most are ‘inexpensive’.
  - Amortized cost is the average cost over all operations.
  - There is no probability distribution or randomness.
Amortized Analysis Review

- Considering a sequence of $m$ operations for sufficiently large $m$:
  - Some operations are more ‘expensive’ and most are ‘inexpensive’.
  - Amortized cost is the average cost over all operations.
  - There is no probability distribution or randomness.
- We saw the amortized number of flips when incrementing a number $m$ times is $\Theta(1)$:
  - Some increment operation need $\Theta(\log m)$ flips while most operation take less flips.
  - On average, each operation needs $\Theta(1)$ flips.
There are three frameworks for amortized analysis.

**Aggregate method:**
- Sum the total cost of \( m \) operations
- Divide by \( m \) to get the amortized cost
- This is what we did for bit flips
Methods for Amortized Analysis

There are three frameworks for amortized analysis.

- **Aggregate method:**
  - Sum the total cost of $m$ operations
  - Divide by $m$ to get the amortized cost
  - This is what we did for bit flips

- **Accounting method**
  - Analogy with a bank account, where there are fixed deposits and variable withdrawals
Methods for Amortized Analysis

- There are three frameworks for amortized analysis.
  - **Aggregate method:**
    - Sum the total cost of $m$ operations
    - Divide by $m$ to get the amortized cost
    - This is what we did for bit flips
  - **Accounting method**
    - Analogy with a bank account, where there are fixed deposits and variable withdrawals
  - **Potential method**
    - Define amortized cost through potential function which maps the sequence of operations to an integer
Methods for Amortized Analysis

- There are three frameworks for amortized analysis.

  **Aggregate method:**
  - Sum the total cost of $m$ operations
  - Divide by $m$ to get the amortized cost
  - This is what we did for bit flips

  **Accounting method**
  - Analogy with a bank account, where there are fixed deposits and variable withdrawals

  **Potential method**
  - Define amortized cost through potential function which maps the sequence of operations to an integer

- Let’s review these methods with an example!
Dynamic Arrays

- Problem: implement a stack stored in an array to support push (insert) operations.
- The problem is *online* in the sense that we do not know how many operations to expect.
Problem: implement a stack stored in an array to support push (insert) operations.

The problem is online in the sense that we do not know how many operations to expect.

How large the array should be? There is a trade-off:

- Larger array: less likely to run out of space, more unused/wasted memory
- Smaller array: more likely to run out of space, less unused/wasted memory
Dynamic Arrays

- Possible solution: allocate an array of size $a = 2n$.
- If the array runs out of space ($n > a$):
  - allocate a new array of size $2n$
  - copy all $n$ items to the new array

  $i$ operation
Dynamic Arrays

- Possible solution: allocate an array of size \( a = 2n \).

- If the array runs out of space \((n > a)\):
  - allocate a new array of size \( a \cdot 2n \)
  - copy all \( n \) items to the new array

\( i \) operation
Dynamic Arrays

- Possible solution: allocate an array of size $a = 2n$.
- If the array runs out of space ($n > a$):
  - allocate a new array of size $a = 2n$
  - copy all $n$ items to the new array

\[
\begin{array}{c|c}
  i & \text{operation} \\
  1 & \text{insert}(a)
\end{array}
\]
Dynamic Arrays

Possible solution: allocate an array of size $a = 2n$.

If the array runs out of space ($n > a$):
- allocate a new array of size $a = 2n$
- copy all $n$ items to the new array

$i$  operation
1  insert(a)
2  insert(b)  no space: allocate array of size 2, copy 1 item
Dynamic Arrays

- Possible solution: allocate an array of size \( a = 2n \).

- If the array runs out of space \( (n > a) \):
  - allocate a new array of size \( 2n \)
  - copy all \( n \) items to the new array

<table>
<thead>
<tr>
<th>( i )</th>
<th>operation</th>
<th>insertion condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>insert(a)</td>
<td>no space: allocate array of size 2, copy 1 item</td>
</tr>
<tr>
<td>2</td>
<td>insert(b)</td>
<td>no space: allocate array of size 4, copy 2 item</td>
</tr>
<tr>
<td>3</td>
<td>insert(c)</td>
<td></td>
</tr>
</tbody>
</table>
Dynamic Arrays

Possible solution: allocate an array of size \( a = 2n \).

If the array runs out of space \((n > a)\):

- allocate a new array of size \( a 2n \)
- copy all \( n \) items to the new array

<table>
<thead>
<tr>
<th>( i )</th>
<th>operation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>insert(a)</td>
</tr>
<tr>
<td>2</td>
<td>insert(b)</td>
</tr>
<tr>
<td></td>
<td>no space: allocate array of size 2, copy 1 item</td>
</tr>
<tr>
<td>3</td>
<td>insert(c)</td>
</tr>
<tr>
<td></td>
<td>no space: allocate array of size 4, copy 2 item</td>
</tr>
<tr>
<td>4</td>
<td>insert(d)</td>
</tr>
</tbody>
</table>
Dynamic Arrays

- Possible solution: allocate an array of size $a = 2^n$.
- If the array runs out of space ($n > a$):
  - allocate a new array of size $2a$
  - copy all $n$ items to the new array

<table>
<thead>
<tr>
<th>$i$</th>
<th>operation</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>insert(a)</td>
<td>$a$</td>
</tr>
<tr>
<td>2</td>
<td>insert(b)</td>
<td>$a$ $b$</td>
</tr>
<tr>
<td>3</td>
<td>insert(c)</td>
<td>$a$ $b$ $c$</td>
</tr>
<tr>
<td>4</td>
<td>insert(d)</td>
<td>$a$ $b$ $c$ $d$</td>
</tr>
<tr>
<td>5</td>
<td>insert(e)</td>
<td>$a$ $b$ $c$ $d$ $e$</td>
</tr>
</tbody>
</table>

- no space: allocate array of size 2, copy 1 item
- no space: allocate array of size 4, copy 2 item
- no space: allocate array of size 8, copy 4 item
Dynamic Arrays

Possible solution: allocate an array of size $a = 2n$.

If the array runs out of space ($n > a$):

- allocate a new array of size $a = 2n$
- copy all $n$ items to the new array

<table>
<thead>
<tr>
<th>$i$</th>
<th>operation</th>
<th>operation details</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>insert(a)</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>insert(b)</td>
<td>no space: allocate array of size 2, copy 1 item</td>
</tr>
<tr>
<td>3</td>
<td>insert(c)</td>
<td>no space: allocate array of size 4, copy 2 item</td>
</tr>
<tr>
<td>4</td>
<td>insert(d)</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>insert(e)</td>
<td>no space: allocate array of size 8, copy 4 item</td>
</tr>
<tr>
<td>6</td>
<td>insert(f)</td>
<td></td>
</tr>
</tbody>
</table>
Dynamic Arrays

- Possible solution: allocate an array of size $a = 2n$.

- If the array runs out of space ($n > a$):
  - allocate a new array of size $a = 2n$
  - copy all $n$ items to the new array

<table>
<thead>
<tr>
<th>$i$</th>
<th>operation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>insert(a)</td>
</tr>
<tr>
<td>2</td>
<td>insert(b)</td>
</tr>
<tr>
<td>3</td>
<td>insert(c)</td>
</tr>
<tr>
<td>4</td>
<td>insert(d)</td>
</tr>
<tr>
<td>5</td>
<td>insert(e)</td>
</tr>
<tr>
<td>6</td>
<td>insert(f)</td>
</tr>
<tr>
<td>7</td>
<td>insert(g)</td>
</tr>
</tbody>
</table>

No space: allocate array of size 2, copy 1 item
No space: allocate array of size 4, copy 2 item
No space: allocate array of size 8, copy 4 item
Dynamic Arrays

- Possible solution: allocate an array of size \( a = 2n \).

- If the array runs out of space (\( n > a \)):
  - allocate a new array of size \( a \times 2n \)
  - copy all \( n \) items to the new array

<table>
<thead>
<tr>
<th>( i )</th>
<th>Operation</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>insert(a)</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>insert(b)</td>
<td>no space: allocate array of size 2, copy 1 item</td>
</tr>
<tr>
<td>3</td>
<td>insert(c)</td>
<td>no space: allocate array of size 4, copy 2 item</td>
</tr>
<tr>
<td>4</td>
<td>insert(d)</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>insert(e)</td>
<td>no space: allocate array of size 8, copy 4 item</td>
</tr>
<tr>
<td>6</td>
<td>insert(f)</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>insert(g)</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>insert(h)</td>
<td></td>
</tr>
</tbody>
</table>
Dynamic Arrays

- Possible solution: allocate an array of size $a = 2n$.
- If the array runs out of space ($n > a$):
  - allocate a new array of size $a 2n$
  - copy all $n$ items to the new array

<table>
<thead>
<tr>
<th>i</th>
<th>operation</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>insert(a)</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>insert(b)</td>
<td>no space: allocate array of size 2, copy 1 item</td>
</tr>
<tr>
<td>3</td>
<td>insert(c)</td>
<td>no space: allocate array of size 4, copy 2 item</td>
</tr>
<tr>
<td>4</td>
<td>insert(d)</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>insert(e)</td>
<td>no space: allocate array of size 8, copy 4 item</td>
</tr>
<tr>
<td>6</td>
<td>insert(f)</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>insert(g)</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>insert(h)</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>insert(i)</td>
<td>no space: allocate array of size 16, copy 8 item</td>
</tr>
</tbody>
</table>
Dynamic Arrays

Possible solution: allocate an array of size $a = 2^n$.

If the array runs out of space ($n > a$):

- allocate a new array of size $a = 2^n$
- copy all $n$ items to the new array

<table>
<thead>
<tr>
<th>$i$</th>
<th>operation</th>
<th>no space: allocate array of size</th>
<th>copy $i$ items</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>insert(a)</td>
<td>2, copy 1 item</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>insert(b)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>insert(c)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>insert(d)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>insert(e)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>insert(f)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>insert(g)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>insert(h)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>insert(i)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>insert(j)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Dynamic Arrays

- Possible solution: allocate an array of size $a = 2^n$.
- If the array runs out of space ($n > a$):
  - allocate a new array of size $2^n$
  - copy all $n$ items to the new array

<table>
<thead>
<tr>
<th>$i$</th>
<th>operation</th>
<th>outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>insert(a)</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>insert(b)</td>
<td>no space: allocate array of size 2, copy 1 item</td>
</tr>
<tr>
<td>3</td>
<td>insert(c)</td>
<td>no space: allocate array of size 4, copy 2 item</td>
</tr>
<tr>
<td>4</td>
<td>insert(d)</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>insert(e)</td>
<td>no space: allocate array of size 8, copy 4 item</td>
</tr>
<tr>
<td>6</td>
<td>insert(f)</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>insert(g)</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>insert(h)</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>insert(i)</td>
<td>no space: allocate array of size 16, copy 8 item</td>
</tr>
<tr>
<td>10</td>
<td>insert(j)</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>insert(k)</td>
<td></td>
</tr>
</tbody>
</table>
Dynamic Arrays

- The worst-case cost occurs when the whole array is copied to a new array:
  - $\Theta(n)$ worst-case time per insert.
- Rough estimate: a sequence of $m$ insert operations takes $O(m \cdot n)$ time.
Dynamic Arrays

- The worst-case cost occurs when the whole array is copied to a new array:
  - $\Theta(n)$ worst-case time per insert.
- Rough estimate: a sequence of $m$ insert operations takes $O(m \cdot n)$ time.
  - We can obtain a much better (smaller) bound.
Dynamic Arrays

- The worst-case cost occurs when the whole array is copied to a new array:
  - $\Theta(n)$ worst-case time per insert.

- Rough estimate: a sequence of $m$ insert operations takes $O(m \cdot n)$ time.
  - We can obtain a much better (smaller) bound.

<table>
<thead>
<tr>
<th>$i$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>array size ($a$)</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>4</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>$c(i)$</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>9</td>
<td>1</td>
</tr>
</tbody>
</table>
Dynamic Arrays

The worst-case cost occurs when the whole array is copied to a new array:
- $\Theta(n)$ worst-case time per insert.

Rough estimate: a sequence of $m$ insert operations takes $O(m \cdot n)$ time.
- We can obtain a much better (smaller) bound.

Let $c(i)$ denote the cost of the $i$th insertion (cost = number of insert/copies).

\[
c(i) = \begin{cases} 
i & \text{if } i = 2^k + 1 \text{ for some integer } k \\
1 & \text{if otherwise}
\end{cases}
\]

---

<table>
<thead>
<tr>
<th>$i$</th>
<th>array size (a)</th>
<th>$c(i)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1 2 3 4 5 6 7 8 9 10</td>
<td>1 2 3 1 5 1 1 1 9 1</td>
</tr>
</tbody>
</table>
Aggregate Method for Dynamic Arrays

Aggregate method: find total cost of $m$ operations and divide by $m$

$$c(i) = \begin{cases} 
  i & \text{if } i = 2^k + 1 \text{ for some integer } k \\
  1 & \text{if otherwise}
\end{cases}$$

The amortized cost is hence $\Theta(m/m) = \Theta(1)$.

The aggregate is useful for simple amortized analysis. Sometimes require a different technique to obtain amortized cost.
Aggregate Method for Dynamic Arrays

Aggregate method: find total cost of \( m \) operations and divide by \( m \)

\[
c(i) = \begin{cases} 
i & \text{if } i = 2^k + 1 \text{ for some integer } k \\
1 & \text{if otherwise}
\end{cases}
\]

Cost of \( m \) insertions

\[
\sum_{i=1}^{m} c(i) \leq m \underbrace{\sum_{j=0}^{[\log(m-1)]} 2^j}_{\text{insert new item}} + \underbrace{\sum_{j=0}^{[\log(m-1)]} 2^j}_{\text{copy old items to new array}}
\]

\[
= m + 2^{[\log(m-1)]+1} - 1 \\
\leq m + 2^{\log m + 1} - 1 \\
= m + 2m - 1 \\
= 3m - 1 \\
\in \Theta(m)
\]
Aggregate Method for Dynamic Arrays

- Aggregate method: find total cost of \( m \) operations and divide by \( m \)

\[
c(i) = \begin{cases} 
  i & \text{if } i = 2^k + 1 \text{ for some integer } k \\
  1 & \text{if otherwise}
\end{cases}
\]

Cost of \( m \) insertions = \( \sum_{i=1}^{m} c(i) \) ≤ \( m \) insert new item + \( \sum_{j=0}^{[\log(m-1)]} 2^j \) copy old items to new array

\[
= m + 2^{[\log(m-1)]} + 1 - 1 \\
\leq m + 2^{\log m + 1} - 1 \\
= m + 2m - 1 \\
= 3m - 1 \\
\in \Theta(m)
\]

- The amortized cost is hence \( \frac{\Theta(m)}{m} = \Theta(1) \)
Aggregate Method for Dynamic Arrays

- Aggregate method: find total cost of $m$ operations and divide by $m$

$$c(i) = \begin{cases} 
  i & \text{if } i = 2^k + 1 \text{ for some integer } k \\
  1 & \text{if otherwise}
\end{cases}$$

Cost of $m$ insertions = $\sum_{i=1}^{m} c(i) \leq m + \sum_{j=0}^{[\log(m-1)]} 2^j$

$$= m + 2^{[\log(m-1)]+1} - 1$$
$$\leq m + 2^{\log m+1} - 1$$
$$= m + 2m - 1$$
$$= 3m - 1$$
$$\in \Theta(m)$$

- The amortized cost is hence $\frac{\Theta(m)}{m} = \Theta(1)$
- The aggregate is useful for simple amortized analysis.
- Sometimes require a different technique to obtain amortized cost.
Accounting Method

Assume you want to prove that your average (amortized) daily cost is no more than 100$.

In \( m \) consecutive days your expenditure has been at most 100$, the amortized cost at most 100$. 
Accounting Method

Assume you want to prove that your average (amortized) daily cost is no more than 100$.

Some days you might spend much more but on average it is at most 100$.
Accounting Method

- Assume you want to prove that your average (amortized) daily cost is no more than 100$.
  - Some days you might spend much more but on average it is at most 100$
- One way to do that is to assume every day 100$ is deposited into your account
- On days which you spend more than 100$, you should use accumulated credit from previous days
Accounting Method

- Assume you want to prove that your average (amortized) daily cost is no more than 100$.
  - Some days you might spend much more but on average it is at most 100$

- One way to do that is to assume every day 100$ is deposited into your account

- On days which you spend more than 100$, you should use accumulated credit from previous days

- If your balance remains positive at the end of each day, your average cost is at most 100$
  - In $m$ consecutive days your expenditure has been at most $100m \rightarrow$ amortized cost at most 100$. 
Accounting Method

Accounting method overview:

- Each operation deposits a fixed credit into an account (This amount is an upper bound on the amortized cost.)
- Each operation uses ‘credit’ to pay its cost
- Inexpensive operations save more than their cost
- Expensive operations cost more more than they save
- Account must remain positive
Accounting Method for Dynamic Arrays

- We prove the amortized cost for insertion is 3

\[ a \rightarrow a \rightarrow a \rightarrow a \rightarrow a \]

<table>
<thead>
<tr>
<th>( i )</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>array size (( a ))</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>4</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>( c(i) )</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>9</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>total deposited</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>15</th>
<th>18</th>
<th>21</th>
<th>24</th>
<th>27</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>total spent</td>
<td>1</td>
<td>3</td>
<td>6</td>
<td>7</td>
<td>12</td>
<td>13</td>
<td>14</td>
<td>15</td>
<td>26</td>
<td>27</td>
<td></td>
</tr>
<tr>
<td>available credit</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>5</td>
<td>3</td>
<td>5</td>
<td>7</td>
<td>9</td>
<td>1</td>
<td>3</td>
<td></td>
</tr>
</tbody>
</table>
Accounting Method for Dynamic Arrays

- We prove the amortized cost for insertion is 3
  - Each operation deposits $3
  - Each write/move operation costs $1

<table>
<thead>
<tr>
<th>$i$</th>
<th>array size ($a$)</th>
<th>$c$($i$)</th>
<th>total deposited</th>
<th>total spent</th>
<th>available credit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1 2 3 4 5 6 7 8 9 10</td>
<td>1 2 3 1 5 1 1 1 9 1</td>
<td>3 6 9 12 15 18 21 24 27 30</td>
<td>1 3 6 7 12 13 14 15 26 27</td>
<td>2 3 3 5 3 5 7 9 1 3</td>
</tr>
</tbody>
</table>
Accounting Method for Dynamic Arrays

- We prove the amortized cost for insertion is 3
  - Each operation deposits $3
  - Each write/move operation costs $1
  - Inexpensive insertion deposits $3 and spends $1 = $2 saved

\[
\text{Number of consecutive inexpensive insertions before expensive insertion: } \frac{m}{2} - 1 \rightarrow 2\left(\frac{m}{2} - 1\right) = (m - 2) \text{ accumulated credit since last expensive insertion}
\]

\[m - 2 > m - 3 \rightarrow \text{account remains positive}\]
Accounting Method for Dynamic Arrays

- We prove the amortized cost for insertion is 3
  - Each operation deposits $3
  - Each write/move operation costs $1
  - Inexpensive insertion deposits $3 and spends $1 = $2 saved
  - Expensive insertion deposits $3 and spends $m → $ (m - 3) spent

<table>
<thead>
<tr>
<th>$i$</th>
<th>array size $(a)$</th>
<th>$c(i)$</th>
<th>total deposited</th>
<th>total spent</th>
<th>available credit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1 2 3 4 5 6 7 8 9 10</td>
<td>1 2 3 1 5 1 1 1 9 1</td>
<td>3 6 9 12 15 18 21 24 27 30</td>
<td>1 3 6 7 12 13 14 15 26 27</td>
<td>2 3 3 5 3 5 7 9 1 3</td>
</tr>
</tbody>
</table>
Accounting Method for Dynamic Arrays

- We prove the amortized cost for insertion is 3.
  - Each operation deposits $3.
  - Each write/move operation costs $1.
  - Inexpensive insertion deposits $3 and spends $1 = $2 saved.
  - Expensive insertion deposits $3 and spends $m → $(m - 3)$ spent.
  - Number of consecutive inexpensive insertions before expensive insertion: $m/2 - 1$.
  - → $2(m/2 - 1) = $(m - 2) accumulated credit since last expensive insertion.

<table>
<thead>
<tr>
<th>$i$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>array size $(a)$</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>4</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>$c(i)$</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td>total deposited</td>
<td>3</td>
<td>6</td>
<td>9</td>
<td>12</td>
<td>15</td>
<td>18</td>
<td>21</td>
<td>24</td>
<td>27</td>
<td>30</td>
</tr>
<tr>
<td>total spent</td>
<td>1</td>
<td>3</td>
<td>6</td>
<td>7</td>
<td>12</td>
<td>13</td>
<td>14</td>
<td>15</td>
<td>26</td>
<td>27</td>
</tr>
<tr>
<td>available credit</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>5</td>
<td>3</td>
<td>5</td>
<td>7</td>
<td>9</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>
Accounting Method for Dynamic Arrays

- We prove the amortized cost for insertion is 3
  - Each operation deposits $3
  - Each write/move operation costs $1
  - Inexpensive insertion deposits $3 and spends $1 = $2 saved
  - Expensive insertion deposits $3 and spends $m \rightarrow $(m - 3) spent
  - Number of consecutive inexpensive insertions before expensive insertion: $m/2 - 1$
  - \rightarrow $2(m/2 - 1) = $(m - 2) accumulated credit since last expensive insertion
  - $m - 2 > m - 3 \rightarrow$ account remains positive

<table>
<thead>
<tr>
<th>$i$</th>
<th>array size ($a$)</th>
<th>$c(i)$</th>
<th>total deposited</th>
<th>total spent</th>
<th>available credit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 2 3 4 5 6 7 8 9 10</td>
<td>1 2 3 4 5 1 1 1</td>
<td>3 6 9 12 15 18 21 24 27 30</td>
<td>1 3 6 7 12 13 14 15 26 27</td>
<td>2 3 3 5 3 5 7 9 1 3</td>
</tr>
</tbody>
</table>
Potential method

- Define a potential function $\Phi$ that maps the state of the structure and the index of an operation to an integer

  Potential is basically the available credit in accounting method

  \[
  \hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1)
  \]

- $\hat{c}(i) \rightarrow$ amortized cost of operation $i$
- $c(i) \rightarrow$ actual cost of operation $i$

- Total amortized cost will be total cost plus a constant independent of $m$. 
Potential Method for Dynamic Arrays

- Define the potential to be \( \Phi(i) = 2i - a_i \)
- \( a_i \) denotes the size of the array after operation \( i \)
Potential Method for Dynamic Arrays

- Define the potential to be $\Phi(i) = 2i - a_i$
- $a_i$ denotes the size of the array after operation $i$
- In case of an inexpensive operation, we have $c_i = 1$ and $a_i = a_{i-1}$; (the size of array does not change)
  - the amortized cost will be
  $$\hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1) = 1 + [2i - a_i] - [2(i - 1) - a_{i-1}] = 3$$
Potential Method for Dynamic Arrays

- Define the potential to be $\Phi(i) = 2i - a_i$
- $a_i$ denotes the size of the array after operation $i$
- In case of an inexpensive operation, we have $c_i = 1$ and $a_i = a_{i-1}$; (the size of array does not change)
  - the amortized cost will be
    $$\hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1) = 1 + [2i - a_i] - [2(i - 1) - a_{i-1}] = 3$$
- For expensive operation $i$, table size changes from $a_{i-1} = (i - 1)$ to $a_i = 2(i - 1)$ and we have $c_i = i$
  - the amortized cost will be
    $$\hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1) = i + [2i - a_i] - [2(i - 1) - a_{i-1}]$$
    $$= i + 2i - 2(i - 1) - 2i + 2 + (i - 1) = 3$$
Potential Method for Dynamic Arrays

- Define the potential to be $\Phi(i) = 2i - a_i$
- $a_i$ denotes the size of the array after operation $i$
- In case of an inexpensive operation, we have $c_i = 1$ and $a_i = a_{i-1}$; (the size of array does not change)
  - the amortized cost will be
    \[ \hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1) = 1 + [2i - a_i] - [2(i - 1) - a_{i-1}] = 3 \]
- For expensive operation $i$, table size changes from $a_{i-1} = (i - 1)$ to $a_i = 2(i - 1)$ and we have $c_i = i$.
  - the amortized cost will be
    \[ \hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1) = i + [2i - a_i] - [2(i - 1) - a_{i-1}] \\
    = i + 2i - 2(i - 1) - 2i + 2 + (i - 1) = 3 \]
- Potential method is often the strongest method for amortized analysis
Methods for Amortized Analysis

- There are three frameworks for amortized analysis.

  **Aggregate method:**
  - Sum the total cost of \( m \) operations
  - Divide by \( m \) to get the amortized cost

  **Accounting method**
  - Analogy with a bank account, where there are fixed deposits and variable withdrawals

  **Potential method**
  - Define amortized cost through potential function which maps the sequence of operations to an integer

- Let’s review these methods with another example!
Consider a stack with one operation $Op(n, x)$, where $n \geq 0$.

$Op(n, x)$: pop $n$ items from the stack and push $x$ to it.
Special Stacks

Consider a stack with one operation $Op(n, x)$, where $n \geq 0$.

$Op(n, x)$: pop $n$ items from the stack and push $x$ to it.

```
<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>b</td>
<td>c</td>
<td>d</td>
<td>e</td>
<td>f</td>
</tr>
<tr>
<td>a</td>
<td>b</td>
<td>b</td>
<td>a</td>
<td>a</td>
<td>e</td>
</tr>
<tr>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
</tr>
<tr>
<td>h</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
```

```
Special Stacks

Consider a stack with one operation $Op(n, x)$, where $n \geq 0$.

$Op(n, x)$: pop $n$ items from the stack and push $x$ to it.

What is the time complexity of each operation?

- Assume each single push and pop has cost 1 (e.g., stack is implemented using a linked list).
Special Stacks

- Consider a stack with one operation $Op(n, x)$, where $n \geq 0$.

  $Op(n, x)$: pop $n$ items from the stack and push $x$ to it.

- What is the time complexity of each operation?
  - Assume each single push and pop has cost 1 (e.g., stack is implemented using a linked list).
  - Assume $m - 1$ operations pop nothing and the $m$th operation pops everything
  - A single operation can have a cost of $\Theta(m)$ in the worst case.
Consider a stack with one operation $Op(n, x)$, where $n \geq 0$.

$Op(n, x)$: pop $n$ items from the stack and push $x$ to it.

What is the time complexity of each operation?
- Assume each single push and pop has cost 1 (e.g., stack is implemented using a linked list).

Assume $m - 1$ operations pop nothing and the $m$’th operation pops everything
- A single operation can have a cost of $\Theta(m)$ in the worst case.
- The amortized time is much better!
Aggregate Method for Special Stacks

Review of aggregate method:

- Sum the total cost of $m$ consecutive operations
- Divide by $m$ to get the amortized cost

Unlike bit flips and dynamic arrays, we cannot predict the cost of the $i$'th operation.
The aggregate method is limited and cannot help for amortized analysis of special stacks!
Aggregate Method for Special Stacks

- Review of aggregate method:
  - Sum the total cost of $m$ consecutive operations
  - Divide by $m$ to get the amortized cost

- Unlike bit flips and dynamic arrays, we cannot predict the cost of the $i$’th operation.

- The aggregate method is limited and cannot help for amortized analysis of special stacks!

```
  a
  b
  c
```
Accounting Method for Special Stacks

Review of accounting method:

- Each operation comes with a fixed deposit that is added to the account (defines the amortized cost).
- For each operation, we subtract the cost of the operation from the account:
  - Inexpensive operations contribute to the account
  - Expensive operations take away from the account
- If the account is positive after each operation, the amortized cost is at most the fixed deposit.
Accounting Method for Special Stacks

- Review of accounting method:
  - Each operation comes with a **fixed deposit** that is added to the **account** (defines the amortized cost).
  - For each operation, we subtract the cost of the operation from the account
    - Inexpensive operations contribute to the account
    - Expensive operations take away from the account
  - Iff the account is positive after each operation, the amortized cost is at most the fixed deposit.

- Often, the account can be imagined as sum of ‘credits’ assigned to different components of data structure
Accounting Method for Special Stacks

- We prove an amortized cost of 2 per operation $\rightarrow$ assume there is a fixed deposit of 2 per operation.
We prove an amortized cost of 2 per operation → assume there is a fixed deposit of 2 per operation.

Maintain this invariant: there is a credit of 1 for each item in the stack → account is the number of items in the stack.
We prove an amortized cost of 2 per operation → assume there is a fixed deposit of 2 per operation.

Maintain this invariant: there is a credit of 1 for each item in the stack → account is the number of items in the stack.

\[ OP(n, x) \text{ where } n \geq 0: \]
Accounting Method for Special Stacks

- We prove an amortized cost of 2 per operation → assume there is a fixed deposit of 2 per operation.
- Maintain this invariant: there is a credit of 1 for each item in the stack → account is the number of items in the stack.
- $OP(n, x)$ where $n \geq 0$:
  - Pop $n$ items: there is a credit of 1 for each item that is popped; so the cost that the algorithm pays for pops is the same as the consumed credit → account remains positive.
Accounting Method for Special Stacks

- We prove an amortized cost of 2 per operation → assume there is a fixed deposit of 2 per operation.
- Maintain this invariant: there is a credit of 1 for each item in the stack → account is the number of items in the stack.
- $OP(n, x)$ where $n \geq 0$:
  - Pop $n$ items: there is a credit of 1 for each item that is popped; so the cost that the algorithm pays for pops is the same as the consumed credit → account remains positive.
  - Push($x$): there is a cost of 1 and fixed deposit of 2; the extra saving is stored as the credit for the item.
Accounting Method for Special Stacks

- With a fixed deposit of 2 per operation, we showed that the balance remains positive after each operation.
- The balance was the accumulated credits stored in each item in the stack.
- We conclude that the amortized cost of each operation is at most 2.

![Diagram showing operations and balances]
Potential Method for Special Stacks

- Review: Define a potential function $\phi(i)$ which maps the state of the structure after operation $i$ to a positive number.
  - Potential is equivalent to the available credit after each operation in the accounting method.

- Amortized cost is the summation of actual cost and the difference in potential function:
  $$ \hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1) $$
Potential Method for Special Stacks

- Review: Define a potential function $\phi(i)$ which maps the state of the structure after operation $i$ to a positive number.
  - Potential is equivalent to the available credit after each operation in the accounting method.
- Amortized cost is the summation of actual cost and the difference in potential function:
  $$\hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1)$$
- Define the potential to be the number of items in the stack

```
```

```
<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>a</td>
<td>b</td>
<td>c</td>
<td>d</td>
<td>e</td>
<td>f</td>
<td>g</td>
</tr>
<tr>
<td>op(0,a)</td>
<td>op(0,b)</td>
<td>op(0,c)</td>
<td>op(1,d)</td>
<td>op(2,e)</td>
<td>op(0,f)</td>
<td>op(0,g)</td>
<td>op(4,h)</td>
</tr>
</tbody>
</table>
```
Potential Method for Special Stacks

- Review: Define a potential function $\phi(i)$ which maps the state of the structure after operation $i$ to a positive number.
  - Potential is equivalent to the available credit after each operation in the accounting method.
- Amortized cost is the summation of actual cost and the difference in potential function:
  $$\hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1)$$
- Define the potential to be the number of items in the stack
  - Assume operation $i$ is $OP(n, x)$. The actual cost is $c(i) = n + 1$. 

```
 +---+---+---+---+---+---+---+---+
|   | a | b |   | c | d | e | f | g |
+---+---+---+---+---+---+---+---+---+
| op(0,a) | op(0,b) | op(0,c) | op(1,d) | op(2,e) | op(0,f) | op(0,g) | op(4,h) |
```
Potential Method for Special Stacks

- Review: Define a potential function $\phi(i)$ which maps the state of the structure after operation $i$ to a positive number.
  - Potential is equivalent to the available credit after each operation in the accounting method.
- Amortized cost is the summation of actual cost and the difference in potential function:
  \[ \hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1) \]
- Define the potential to be the number of items in the stack
  - Assume operation $i$ is $OP(n,x)$. The actual cost is $c(i) = n + 1$.
  - After the operation, the number of items is increased by $1 - n$, i.e., $\Phi(i) - \Phi(i - 1) = 1 - n$. 

```
<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>a</td>
<td>b</td>
<td></td>
<td>b</td>
<td></td>
<td>d</td>
<td>e</td>
</tr>
<tr>
<td>a</td>
<td>b</td>
<td>a</td>
<td>c</td>
<td>b</td>
<td>a</td>
<td></td>
<td>f</td>
</tr>
<tr>
<td>b</td>
<td>a</td>
<td></td>
<td></td>
<td></td>
<td>e</td>
<td>a</td>
<td></td>
</tr>
<tr>
<td>h</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>e</td>
<td>a</td>
<td>g</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>f</td>
<td>e</td>
<td></td>
</tr>
<tr>
<td>op(0,a)</td>
<td>op(0,b)</td>
<td>op(0,c)</td>
<td>op(1,d)</td>
<td>op(2,e)</td>
<td>op(0,f)</td>
<td>op(0,g)</td>
<td>op(4,h)</td>
</tr>
</tbody>
</table>
```
Potential Method for Special Stacks

- Review: Define a potential function $\phi(i)$ which maps the state of the structure after operation $i$ to a positive number.
  - Potential is equivalent to the available credit after each operation in the accounting method.

- Amortized cost is the summation of actual cost and the difference in potential function:
  $$\hat{c}(i) = c(i) + \Phi(i) - \Phi(i - 1)$$

- Define the potential to be the number of items in the stack
  - Assume operation $i$ is $OP(n, x)$. The actual cost is $c(i) = n + 1$.
  - After the operation, the number of items is increased by $1 - n$, i.e., $\Phi(i) - \Phi(i - 1) = 1 - n$.
  - The amortized cost is $\hat{c}(i) = (n + 1) + (1 - n) = 2$. 

```
   a     b     c     d     e     f     g     h
op(0,a) op(0,b) op(0,c) op(1,d) op(2,e) op(0,f) op(0,g) op(4,h)
```
More Examples of Amortized Analysis

- Fibonacci heaps: similar to binomial heaps except that they have a more ‘relaxed’ structure
  - Most operations can be done in constant time; for some operations, the heap should be restructured.
  - The amortized cost for Insert, ExtractMax, Merge, and IncreaseKey is $O(1)$ (champions for priority queues).
More Examples of Amortized Analysis

- Fibonacci heaps: similar to binomial heaps except that they have a more ‘relaxed’ structure
  - Most operations can be done in constant time; for some operations, the heap should be restructured.
  - The amortized cost for Insert, ExtractMax, Merge, and IncreaseKey is $O(1)$ (champions for priority queues).

- Dynamic lists and arrays
  - Update a self-adjusting linked list with Move-To-Front strategy: applications in data compression
More Examples of Amortized Analysis

• Fibonacci heaps: similar to binomial heaps except that they have a more ‘relaxed’ structure
  • Most operations can be done in constant time; for some operations, the heap should be restructured.
  • The amortized cost for Insert, ExtractMax, Merge, and IncreaseKey is $O(1)$ (champions for priority queues).

• Dynamic lists and arrays
  • Update a self-adjusting linked list with Move-To-Front strategy: applications in data compression
  • Splay trees: dynamic binary trees which move an accessed item closer to the root.
    • Ideal for real-world scenarios where there is locality in accesses
    • Dynamic optimality conjecture: the amortized cost of accessing an item in a splay tree is within a constant ratio of any other tree (a challenging open question).
More Examples of Amortized Analysis

- Fibonacci heaps: similar to binomial heaps except that they have a more ‘relaxed’ structure
  - Most operations can be done in constant time; for some operations, the heap should be restructured.
  - The amortized cost for Insert, ExtractMax, Merge, and IncreaseKey is $O(1)$ (champions for priority queues).

- Dynamic lists and arrays
  - Update a self-adjusting linked list with Move-To-Front strategy: applications in data compression
  - Splay trees: dynamic binary trees which move an accessed item closer to the root.
    - Ideal for real-world scenarios where there is locality in accesses
    - Dynamic optimality conjecture: the amortized cost of accessing an item in a splay tree is within a constant ratio of any other tree (a challenging open question).

- The whole field of online algorithms!