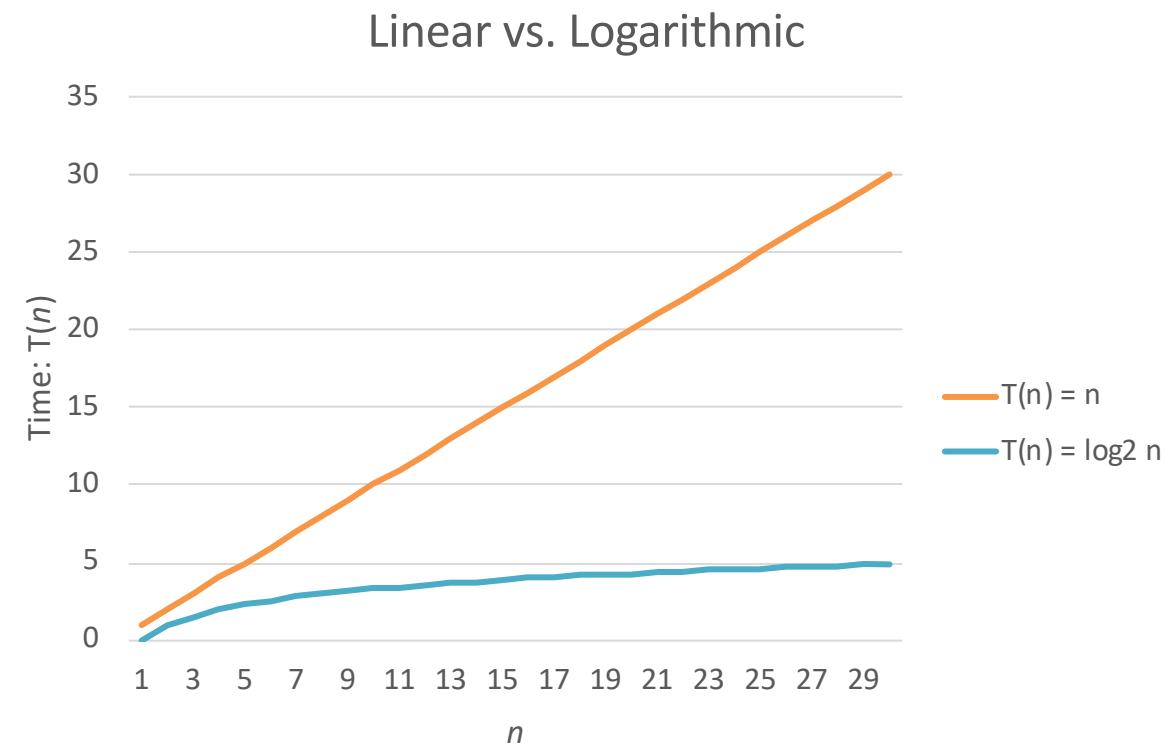


# Sort then Search?

# Recall: Linear and Binary Search

- Find an element of an array
- Linear search:  $O(n)$  time
- Binary search:  $O(\log n)$  time
  - Requires sorted array



# Searching an Array: Sort then Search?

## Linear Search

Total:  $O(n)$

5

Sorting is expensive!  
(compared to searching)

## Sort + Binary Search

Total:  $\Theta(n \log n) + O(\log n) = \Theta(n \log n)$

8

1.6

# Searching an Array: Sort then Search?

2 x Linear Search

$$\text{Total: } 2 \cdot O(n) = O(n)$$



Sort + 2 x Binary Search

$$\text{Total: } \Theta(n \log n) + 2 \cdot O(\log n) = \Theta(n \log n)$$



$$\text{Per Search: } \frac{\Theta(n \log n)}{2} = \Theta(n \log n)$$



Not “real”, but useful!

# Searching an Array: Sort then Search?

$n \times$  Linear Search

$$\text{Total: } n \cdot O(n) = O(n^2)$$



Sort +  $n \times$  Binary Search

$$\text{Total: } \Theta(n \log n) + n \cdot O(\log n) = \Theta(n \log n)$$



$$\text{Per Search: } \frac{\Theta(n \log n)}{n} = \Theta(\log n)$$



*Sorting is worth it if you  
need to search a lot!*

# Side Note: Maintaining a Sorted Array?

- What if you want to insert and remove things?
    - Find where to insert/remove:  $O(\log n)$
    - Inserting/removing in the middle is expensive:  $O(n)$
  - Use a linked list?
    - Insert/remove:  $O(1)$
    - Binary search relies on random access:  $O(n)$
  - Binary search tree!
    - Maintains sorted order (in-order traversal)
    - Search:  $O(\log n)$
    - Insert/remove:  $O(\log n)$
- Use binary search!*
- BST search is basically  
binary search!*

# Summary

- Is it worth it to sort before searching?
  - Only if you do lots of searches after sorting
  - ( $\text{Lots} = \Theta(n)$ )
- Sometimes you need to spend time to save time
  - Do an expensive operation to make future operations cheaper
- Main ideas:
  - Analyze total cost of a *sequence* of operations
  - Report cost per operation (a useful fiction!)

# Coming Up...

## Amortized Analysis

# Amortized Analysis

# Array-Backed List

- A list structure that stores elements in an array
- See:
  - C++ `std::vector`
  - Python list
  - Java `ArrayList`
- To append:
  - If enough space, simply put item in array ( $\Theta(1)$ )
  - If out of space... ( $\Theta(n)$ )
    - Allocate a bigger array ( $\Theta(1)$ )
    - Copy the contents ( $\Theta(n)$ )
    - Delete old array ( $\Theta(1)$ )

$\Theta(n)$

# Complexity Analysis

Worst-case time of appending  $m$  items?

```
vector<size_t> v;  
for (size_t i = 0; i < m; ++i) {  
    v.push_back(i);  
}
```

Are we really  
going to resize for  
every append??

Worst case: resize ( $\Theta(n)$ )  
 $n = i = 0, 1, 2, \dots, m - 1$

Complexity:  $O(1 + 2 + \dots + m - 1) = O\left(\frac{(m - 1)m}{2}\right) = O(m^2)$

# Complexity Analysis

- Say that when we resize, we add  $k$  slots (start with  $k$  slots)
  - Then we resize every  $k$  inserts
- Complexity of  $m$  appends?

- $m \left( \frac{k-1}{k} \right)$  easy appends:  $m \left( \frac{k-1}{k} \right) \cdot \Theta(1) = \Theta(m)$
- $m \frac{1}{k}$  resize appends:  $\Theta \left( k + 2k + \dots + \frac{m}{k} k \right) = \Theta \left( k \left( 1 + 2 + \dots + \frac{m}{k} \right) \right)$  $= \Theta \left( k \frac{\frac{m}{k} \left( \frac{m}{k} + 1 \right)}{2} \right) = \Theta(m^2)$

- Overall:  $\Theta(m) + \Theta(m^2) = \Theta(m^2)$  Comparable to resizing for every append!

# Complexity Analysis

- Say that when we resize, we double the slots (start with 1 slot)
  - Then we resize when there are  $1, 2, 4, 8, \dots = 2^0, 2^1, 2^2, 2^3 \dots$  items
- Complexity of  $m$  appends?
  - How many resizes?
    - How many powers of 2 are less than  $m$ ?
      - $2^x \leq m \rightarrow x \leq \log_2 m$
      - So  $\Theta(\log m)$  resizes
    - $\Theta(m - \log m)$  easy appends:  $\Theta(m - \log m) \cdot \Theta(1) = \Theta(m) \cdot \Theta(1) = \Theta(m)$
    - $\Theta(\log m)$  resize appends:  $\Theta(2^0 + 2^1 + 2^2 + \dots + 2^{\log_2 m}) = \Theta(2^{\log_2 m}) = \Theta(m)$
    - Overall:  $\Theta(m) + \Theta(m) = \Theta(m)$

Better than resizing for every append!

$$\Theta(a^0 + a^1 + a^2 + \dots + a^n) = \Theta(a^n)$$

$\Theta$  because of this  $\leq$

$$\Theta(2^0 + 2^1 + 2^2 + \dots + 2^{\log_2 m}) = \Theta(2^{\log_2 m}) = \Theta(m)$$

# Amortized Analysis

- An *amortized* time is a bound that promises
  - The worst case time of a sequence of operations (starting from “empty”) is bounded by the sum of the amortized times of the individual operations
- The amortized time is *not* how long an operation actually takes!
  - It is the *per operation* time of a sequence of operations

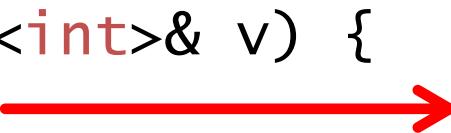
# Amortized Analysis

- Array-Backed List (adding capacity)
  - Cost of appending  $n$  items:  $\Theta(n^2)$
  - Amortized  $\frac{\Theta(n^2)}{n} = \Theta(n)$  insert time
- Array-Backed List (doubling capacity)
  - Cost of appending  $n$  items:  $\Theta(n)$
  - Amortized  $\frac{\Theta(n)}{n} = \Theta(1)$  insert time

# Amortized Analysis

- Amortized times only make sense when starting from “empty”

```
void f(std::vector<int>& v) {  
    v.push_back(0);  
}
```



Can't promise  $O(1)$  for *I* append...  
*v* might be huge and about to resize!

- Our sort + search analysis was not quite an amortized analysis
  - Only promise  $O(\log n)$  per search for one sort and a *lot* of searches
  - Amortized times bound the worst case for any sequence!

# Average-Case Analysis

- Contrast: Average-case analysis
  - For finding “typical” complexity
  - Assign probabilities to different cases
  - Get expected time complexity, given those probabilities
- Amortized analysis
  - For finding aggregate *worst-case* complexities
  - Consider sequences of operations
  - Get time per operation

# Summary

- Array-backed list
  - Store a list in an array, resize as necessary
- Worst-case analysis is misleading
  - The worst case is resizing, but we don't always resize!
- Amortized analysis
  - Rather than summing up individual worst-case complexities...
  - ...Analyze entire sequence of operations (starting from "empty")
  - Report average time per operation
- Amortized time of an operation
  - Time complexity of sequence is bounded by sum of amortized times
- Array-backed lists: amortized  $\Theta(1)$  append

# Coming Up...

## Splay Trees

# Splay Trees: Intro

# Splay Trees

- A splay tree is a self-balancing binary search tree, like
  - Randomized BSTs
  - Red-black trees (and 2-3-4 trees)
- Complexities ( $n$  nodes):
  - Worst-case  $O(n)$  insert and search
  - Amortized  $O(\log n)$  insert and search

# Splay Trees

- What is the worst-case time of the following sequence?
  - Insert  $m$  distinct items into an empty tree
  - Look up each of the  $m$  items
- Tempting:
  - Worst-case  $O(n)$  for each operation so...
  - Inserts:  $O(1 + 2 + \dots + m)$
  - Lookups:  $O(m + m + \dots + m)$
  - Total worst-case complexity:  $O(m^2)$

True!

But too conservative/loose  
It's not going to take this long!

# Splay Trees

- What is the worst-case time of the following sequence?
  - Insert  $m$  distinct items into an empty tree
  - Look up each of the  $m$  items
- Better:
  - Amortized  $O(\log n)$  for each operation so...
  - Inserts:  $O(\log 1 + \log 2 + \dots + \log m)$
  - Lookups:  $O(\log m + \log m + \dots + \log m)$
  - Total worst-case complexity:  $O(m \log m)$

A tighter bound!  
Important: this is not an amortized bound  
It's an actual worst-case bound!

# Splay Trees

- <https://www.cs.usfca.edu/~galles/visualization/SplayTree.html>
- Sort of like insert-at-root
  - But it happens every time
  - Not randomized!
- Changes the tree when you search!
  - Recently found items move to the root
- Overall principle
  - There might be a long branch
  - But if you insert/search there, you make it shorter

# Splay Trees Pros?

- Good worst-case bounds on op. sequences (amortized  $O(\log n)$ )
  - BSTs and randomized BSTs have amortized  $O(n)$  operations)
- No extra bookkeeping
  - Red-black trees and randomized BSTs have more space overhead
- Relatively simple to implement
  - Simpler than red-black trees
  - Slightly more complicated than randomized BSTs
- Locality
  - Recently/frequently found items are cheap to find again

# Splay Tree Cons?

- Worst-case  $O(n)$  time of individual operations
  - Variation in runtime for each insert/search
  - Red-black trees guarantee  $O(\log n)$  worst-case complexity
- Overhead of rotations on every operation
  - BST has no re-balancing overhead
  - Randomized BST and red-black trees only re-balance on insert/delete
- Lookup can change the tree!
  - Seems weird
  - In C++, we expect `exists(const item_t& x)` to be const, but it can't be!
  - (Actually it can be – look up the `mutable` keyword, if you are interested)

# Summary

- Splay Trees
  - Self-balancing binary search tree
  - Worst-case  $O(n)$  insert and search
  - Amortized  $O(\log n)$  insert and search
  - Low space overhead
  - Especially good when there are common/repetitive lookups
- Demo
  - Inserted items move to root
  - Found items move to root
  - Individual operations might be expensive
    - But long branches get pulled up

# Coming Up...

## Splay Tree Details

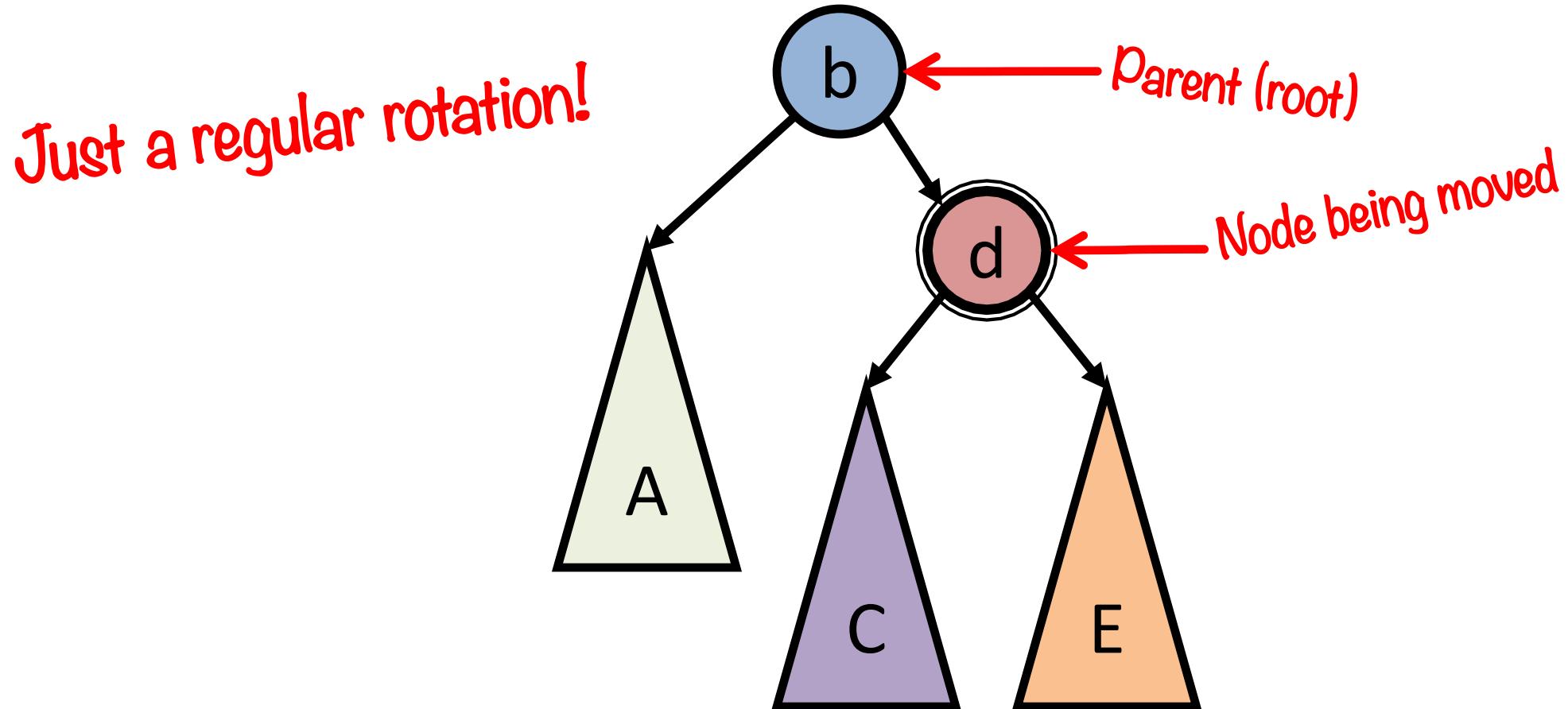
# Splay Trees: Details

# Splay Tree Insertion

- Big picture
  - Perform normal BST insertion
  - Then percolate the new node to the root
    - “Splay” operation
- Splay operation
  - Move new node up 2 levels at a time (double rotations!)
  - When possible, use a special double rotation

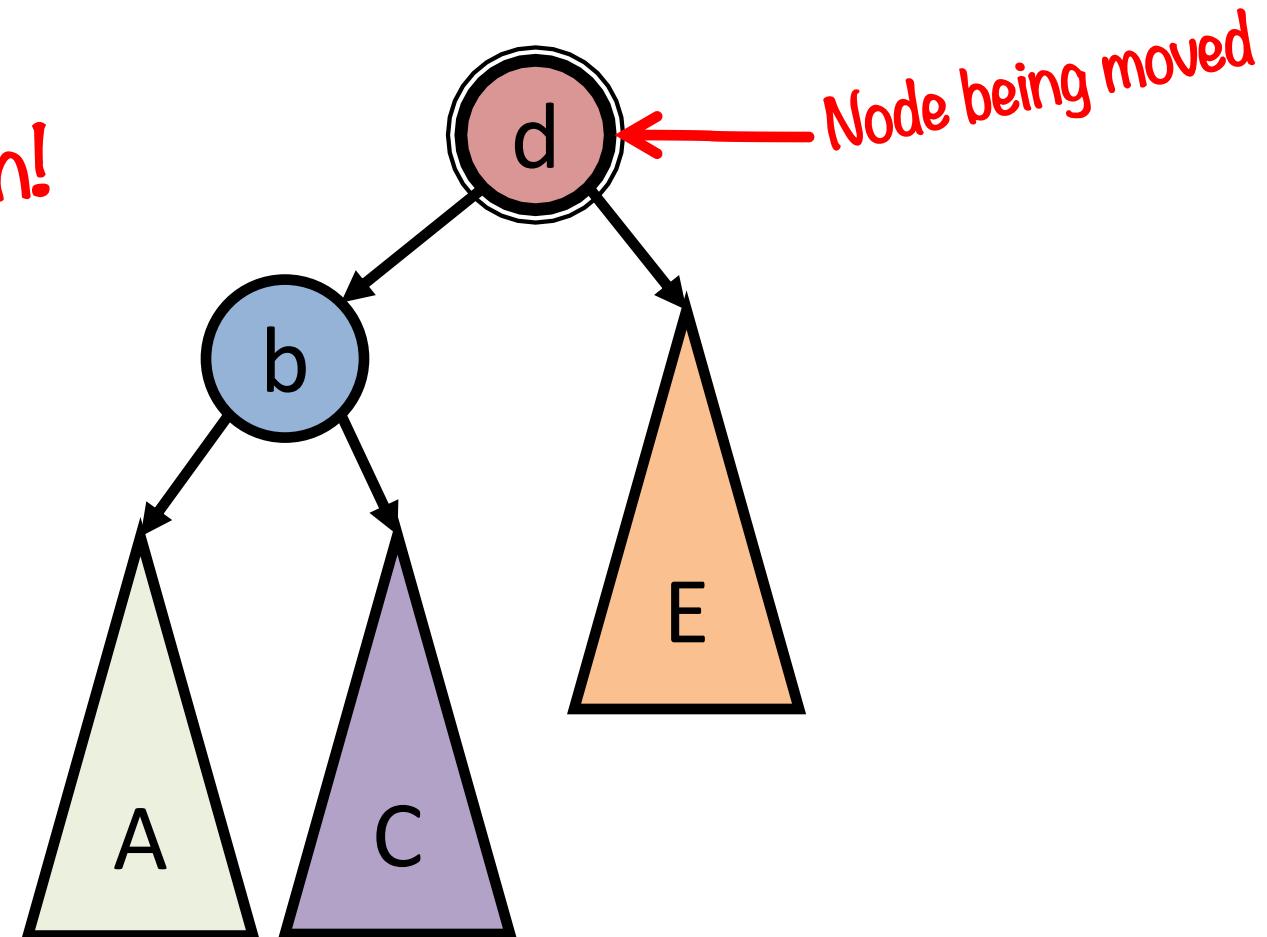
Like insert-at-root!

# Node's parent is root: “zag” operation



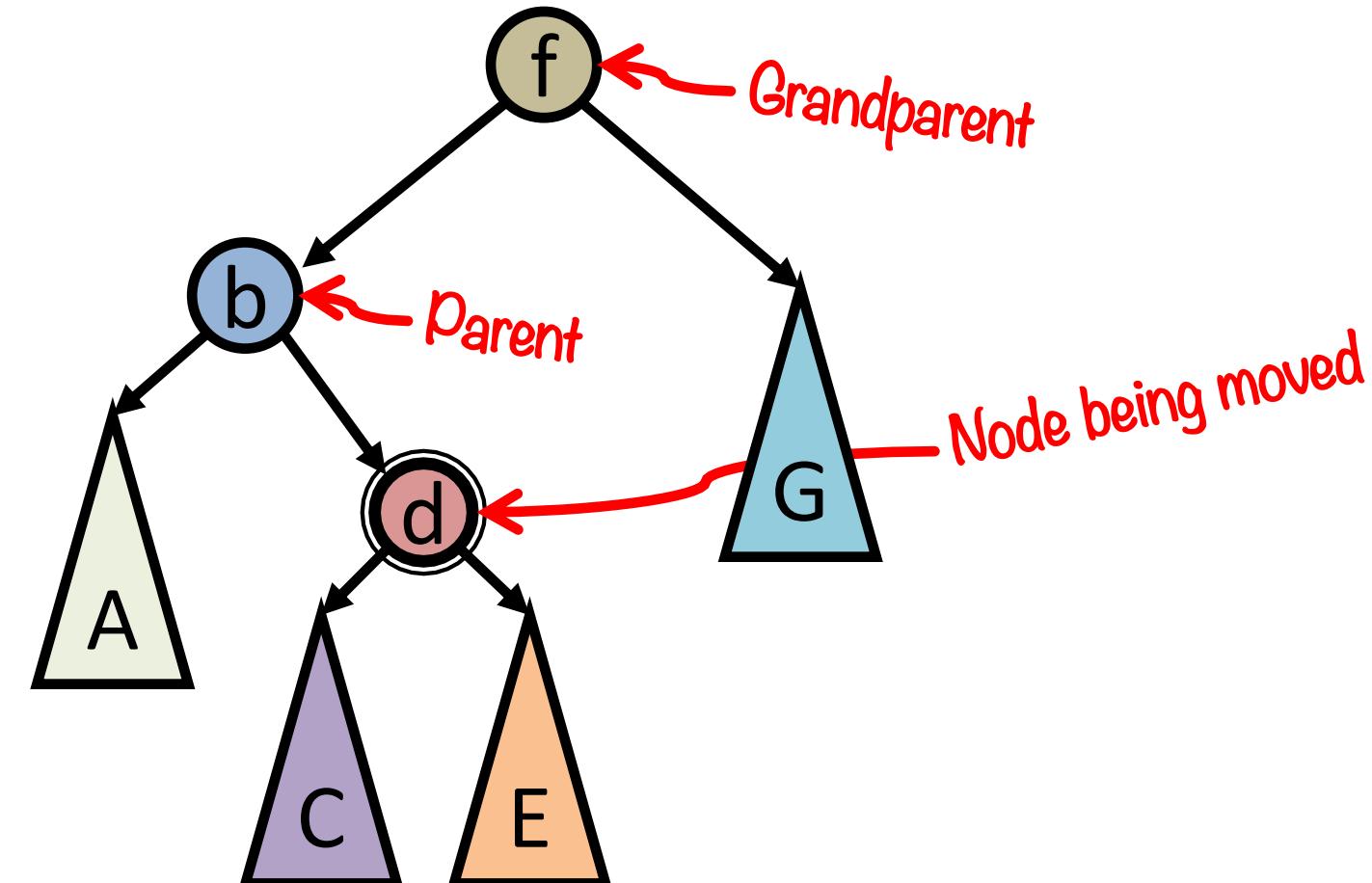
Node's parent is root: “zag” operation

Just a regular rotation!



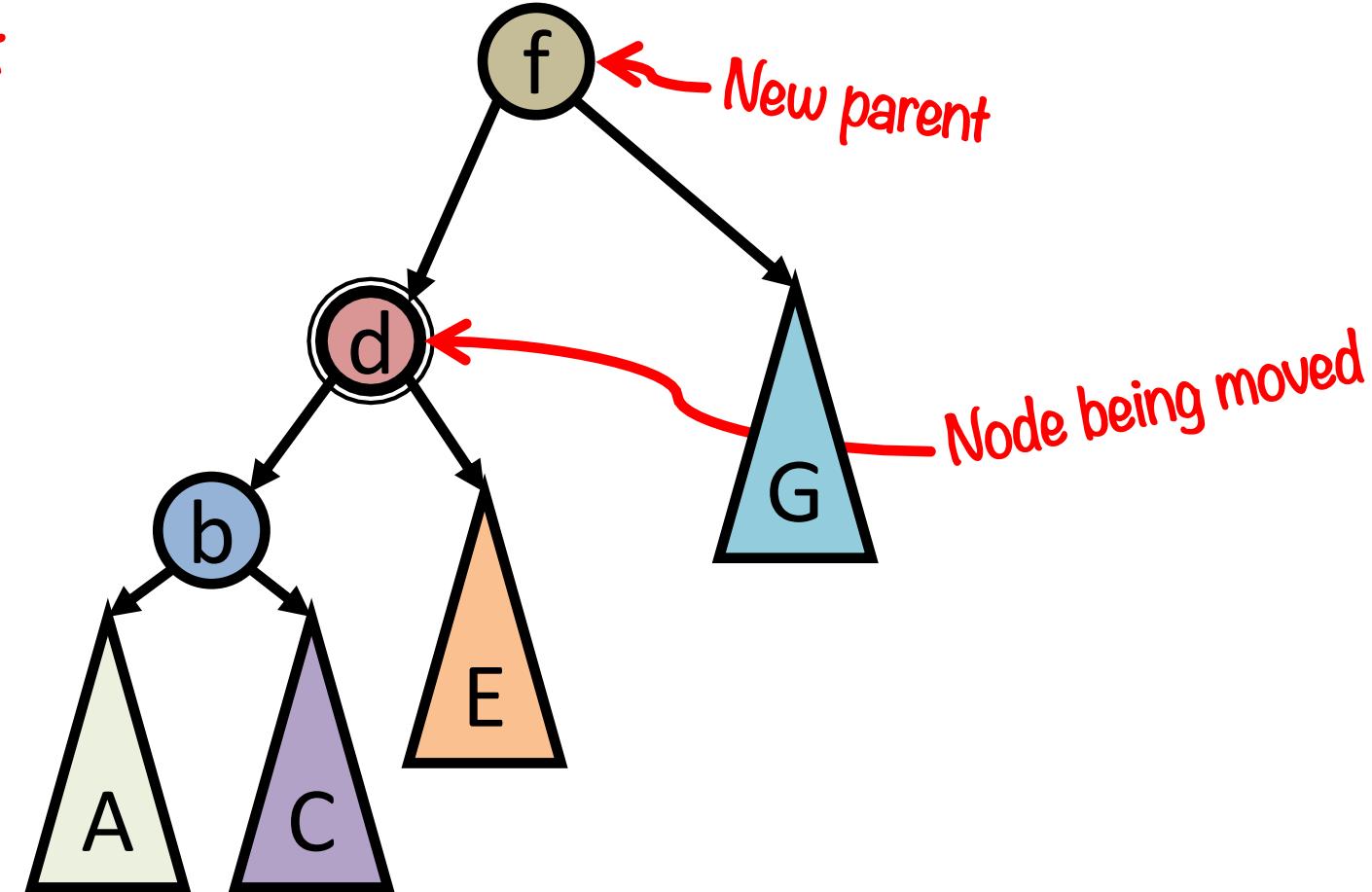
Right child of left child: “zag-zig” operation

Just two regular rotations!



# Right child of left child: “zag-zig” operation

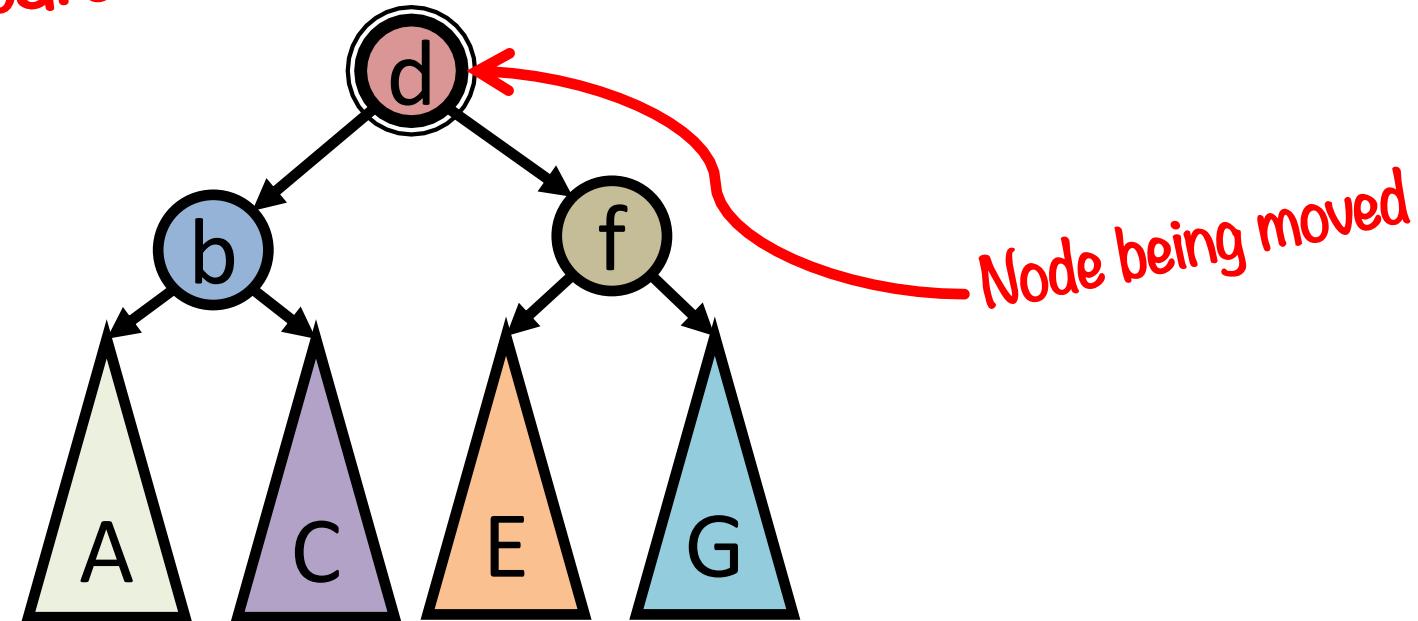
Just two regular rotations!  
1. Rotate on parent



# Right child of left child: “zag-zig” operation

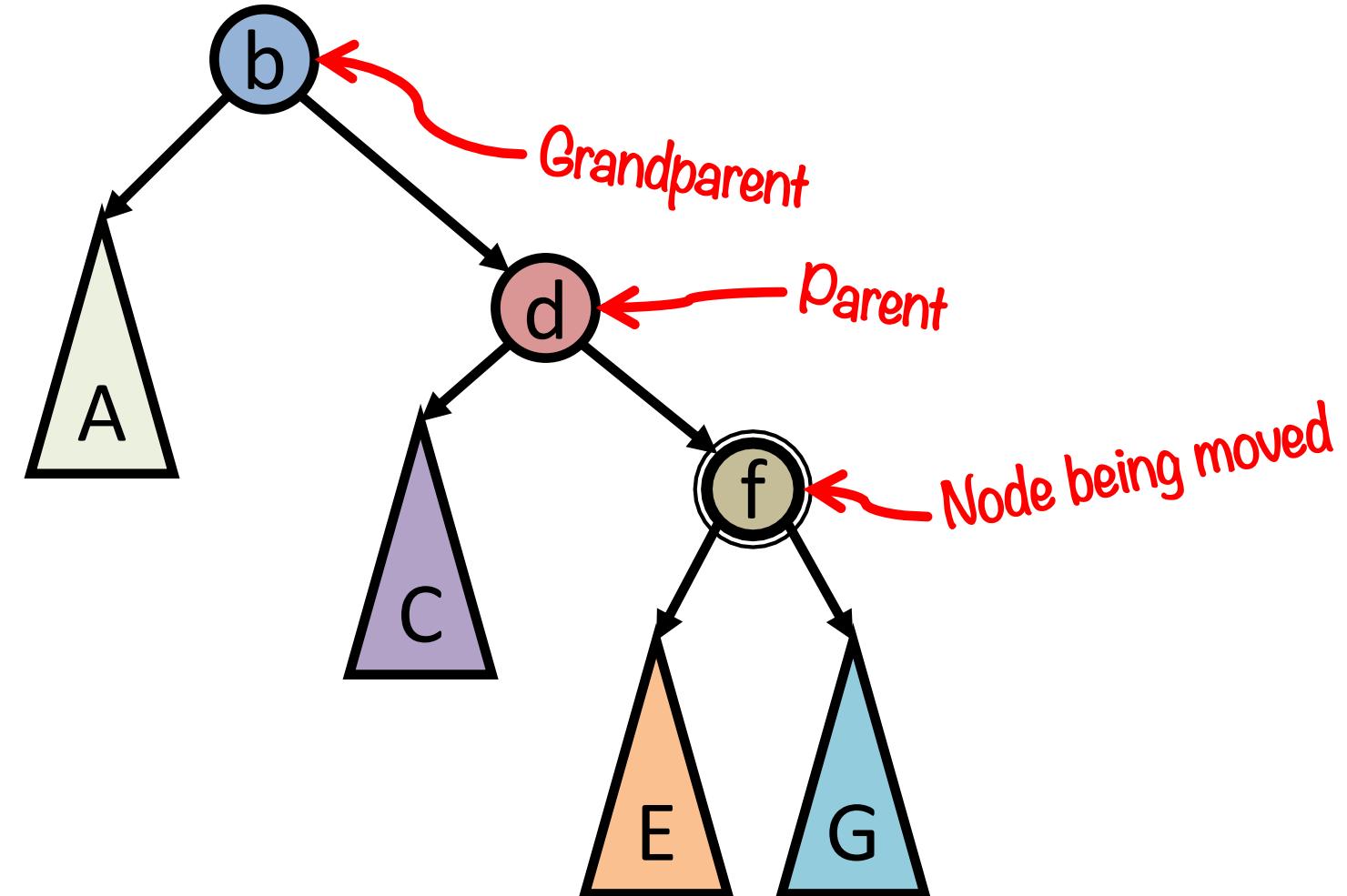
Just two regular rotations!

1. Rotate on parent
2. Rotate on new parent



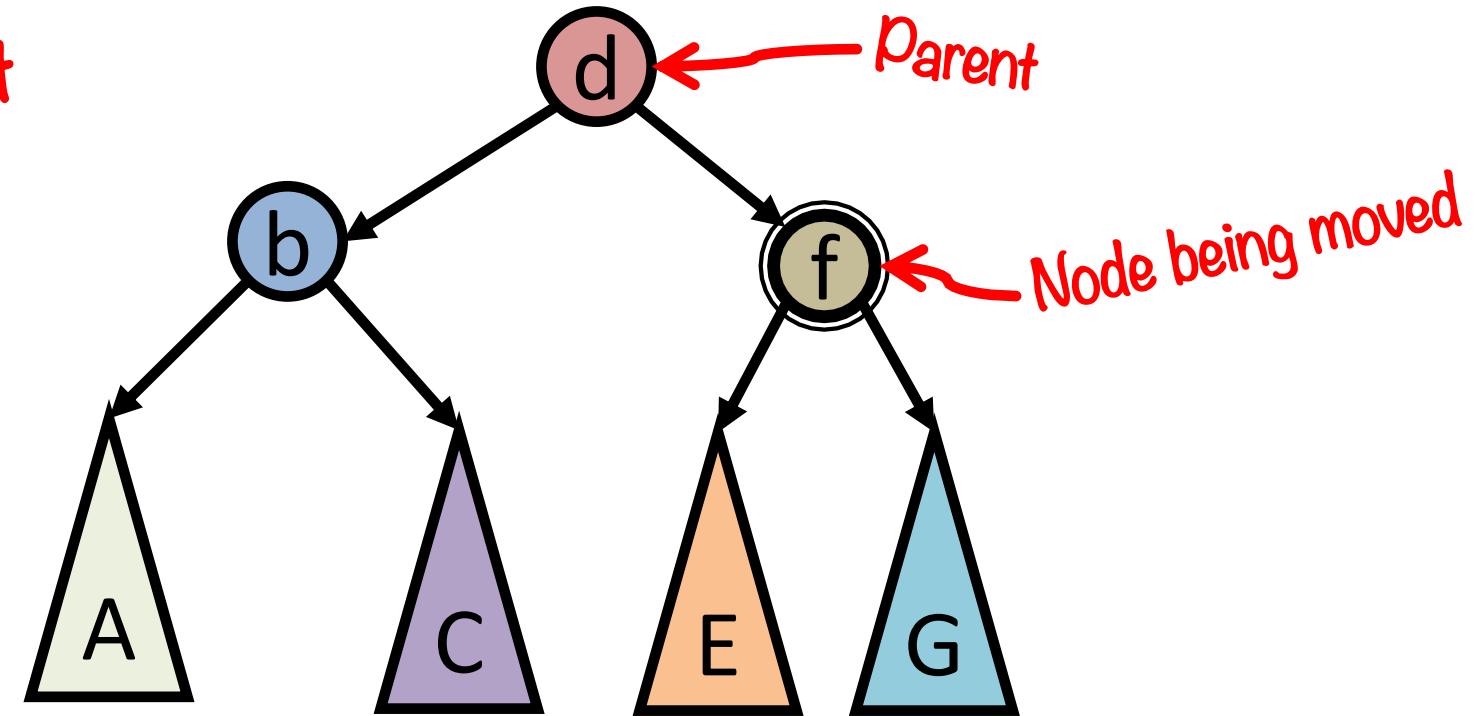
# Right child of right child: “zag-zag” operation

Special to splay trees



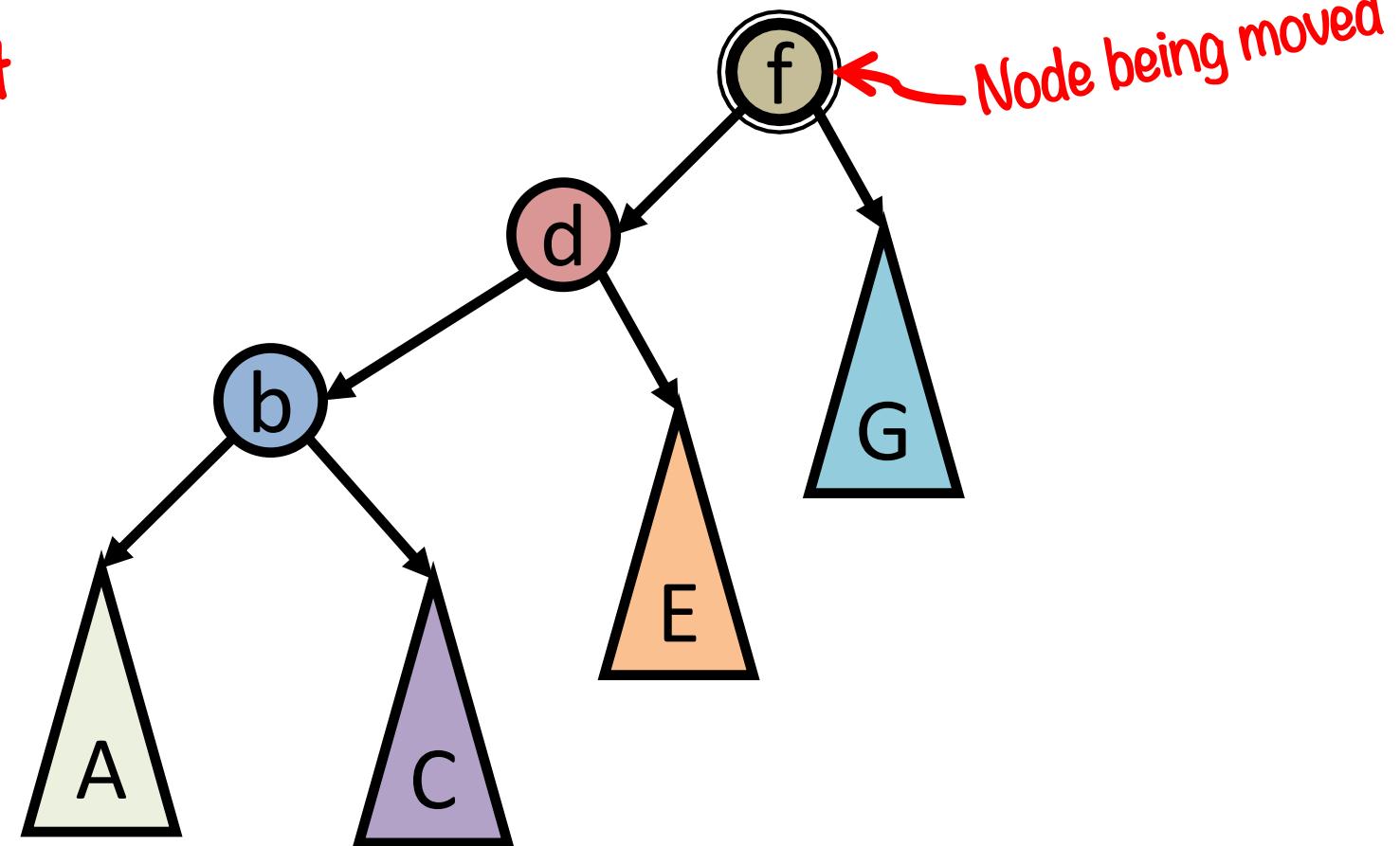
# Right child of right child: “zag-zag” operation

Special to splay trees  
1. Rotate on grandparent



# Right child of right child: “zag-zag” operation

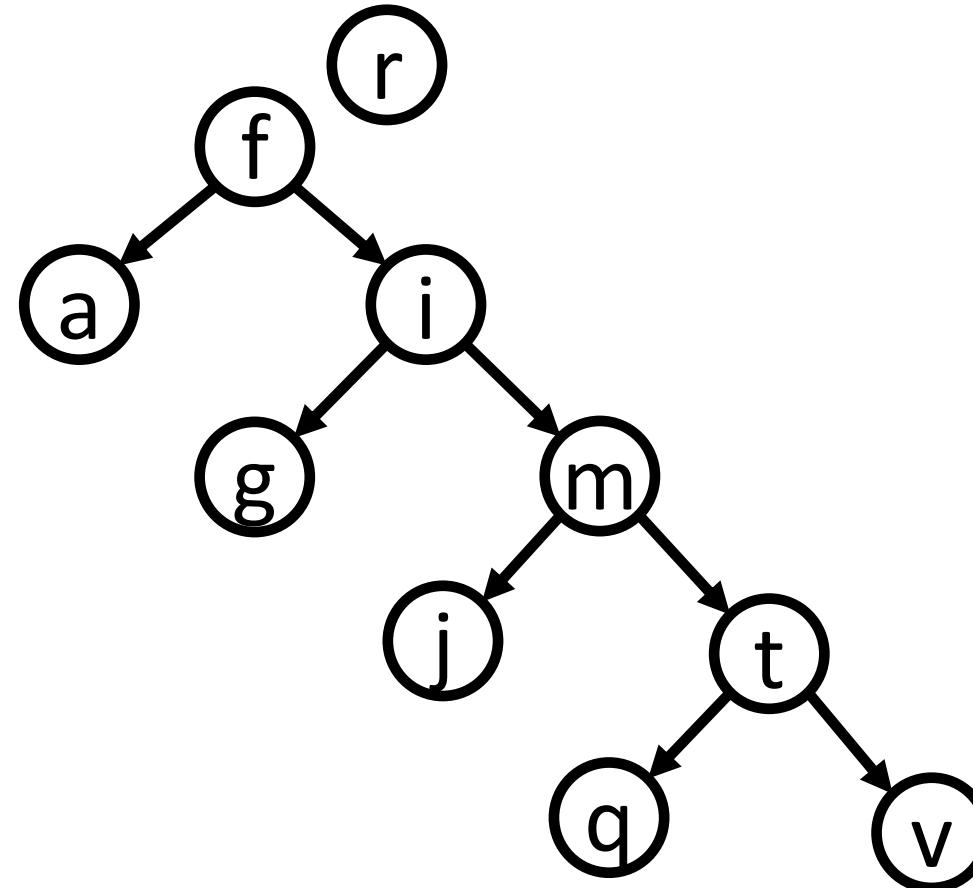
Special to splay trees  
1. Rotate on grandparent  
2. Rotate on parent



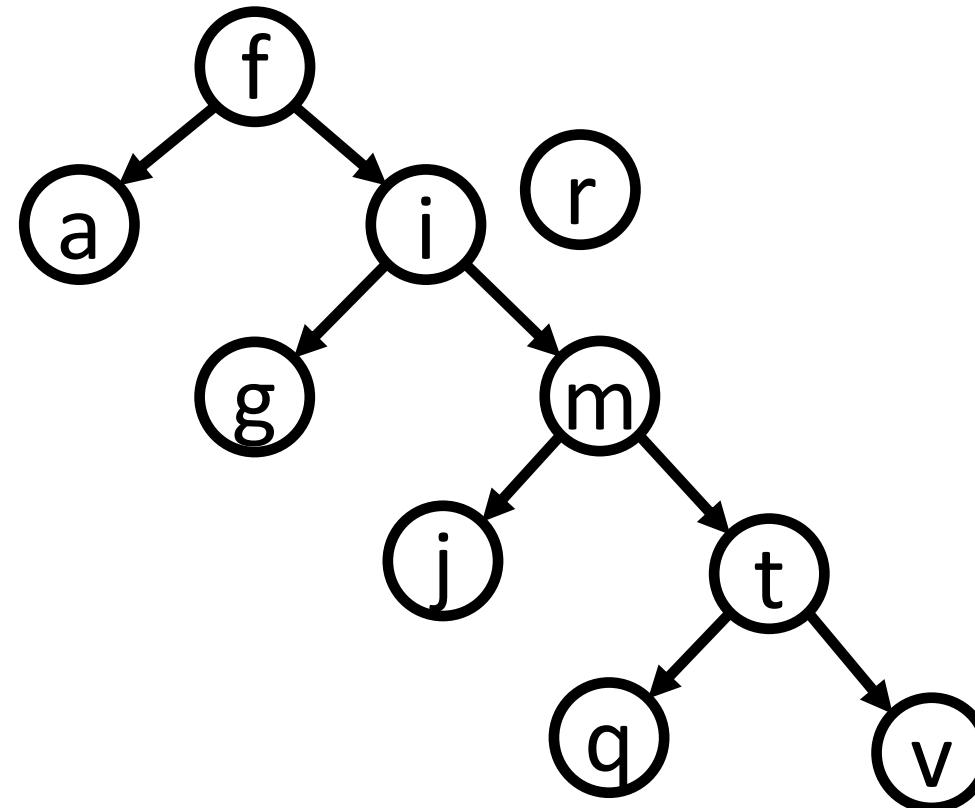
# Splay Tree Operations

- Splay Operation
  - Move the given node to the root
  - Use zig-zig and zag-zag rotations when possible
- Insert
  - Insert as usual
  - Splay new node
- Search
  - Search as usual
  - Splay found node

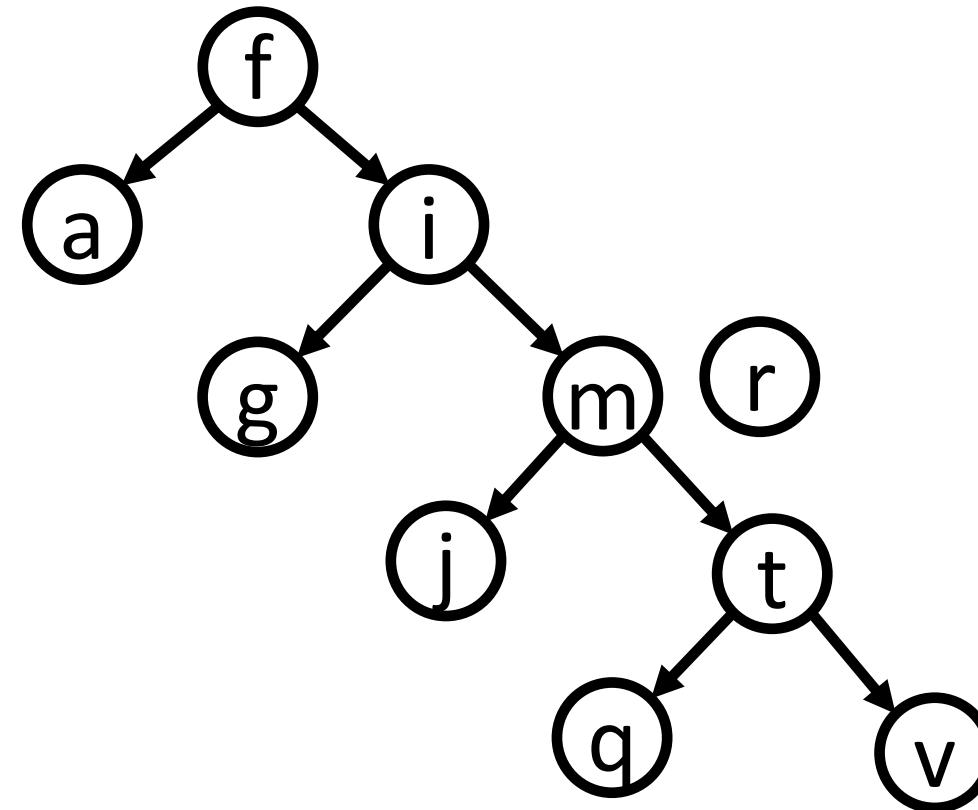
# Example: Insert



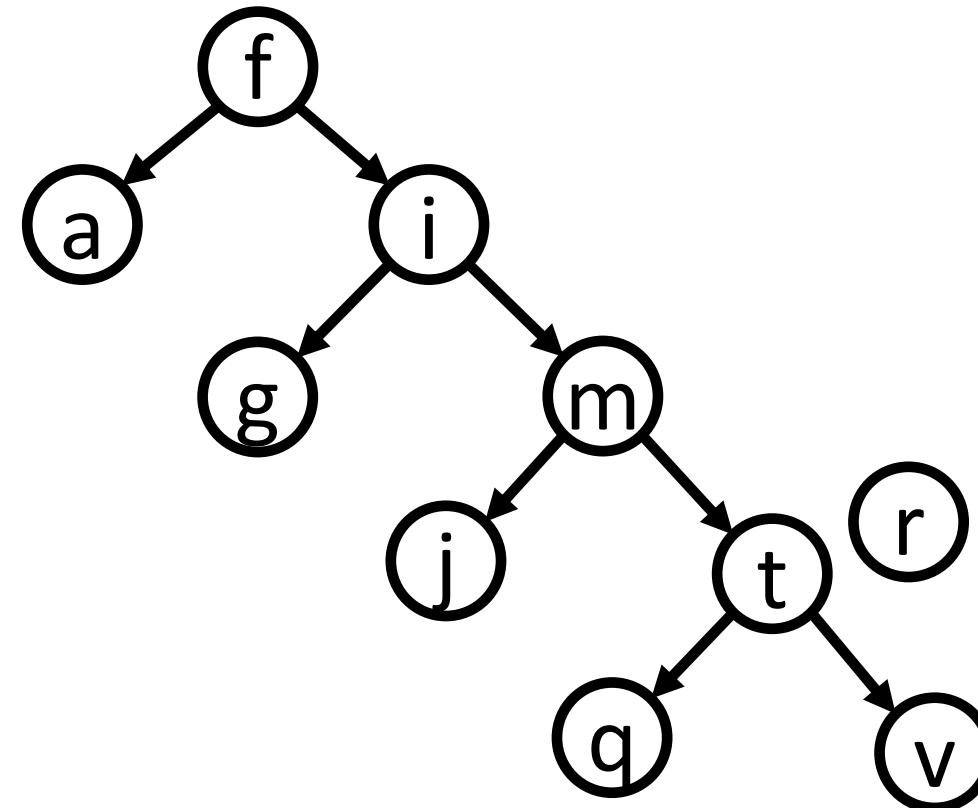
# Example: Insert



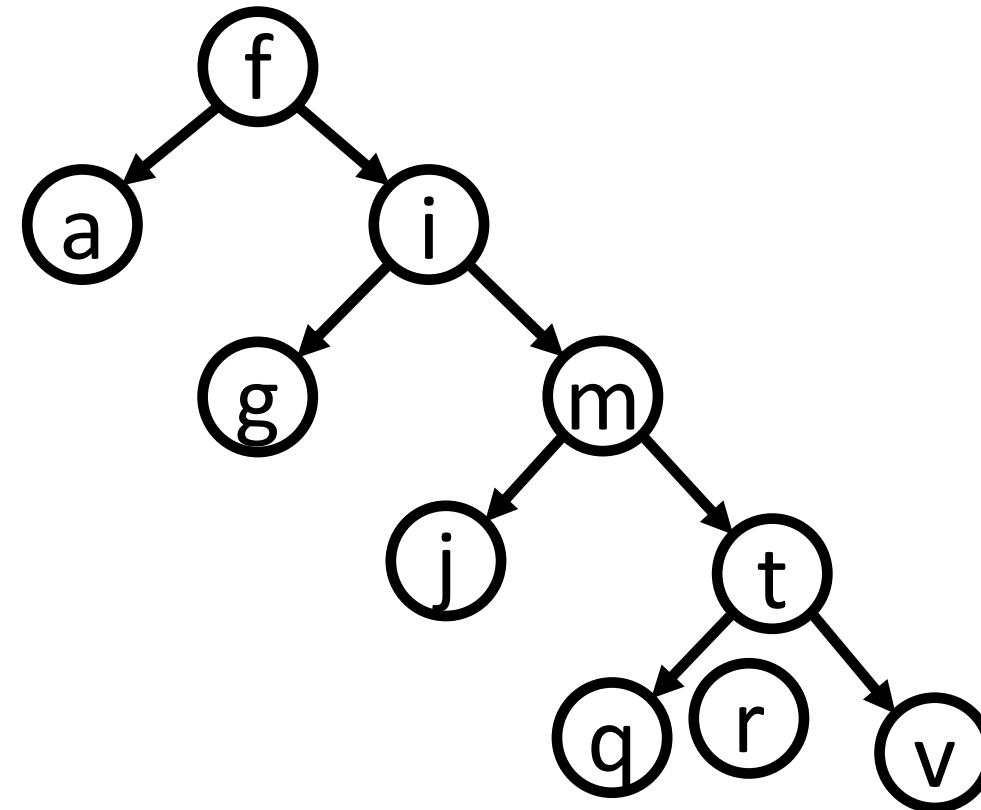
# Example: Insert



# Example: Insert



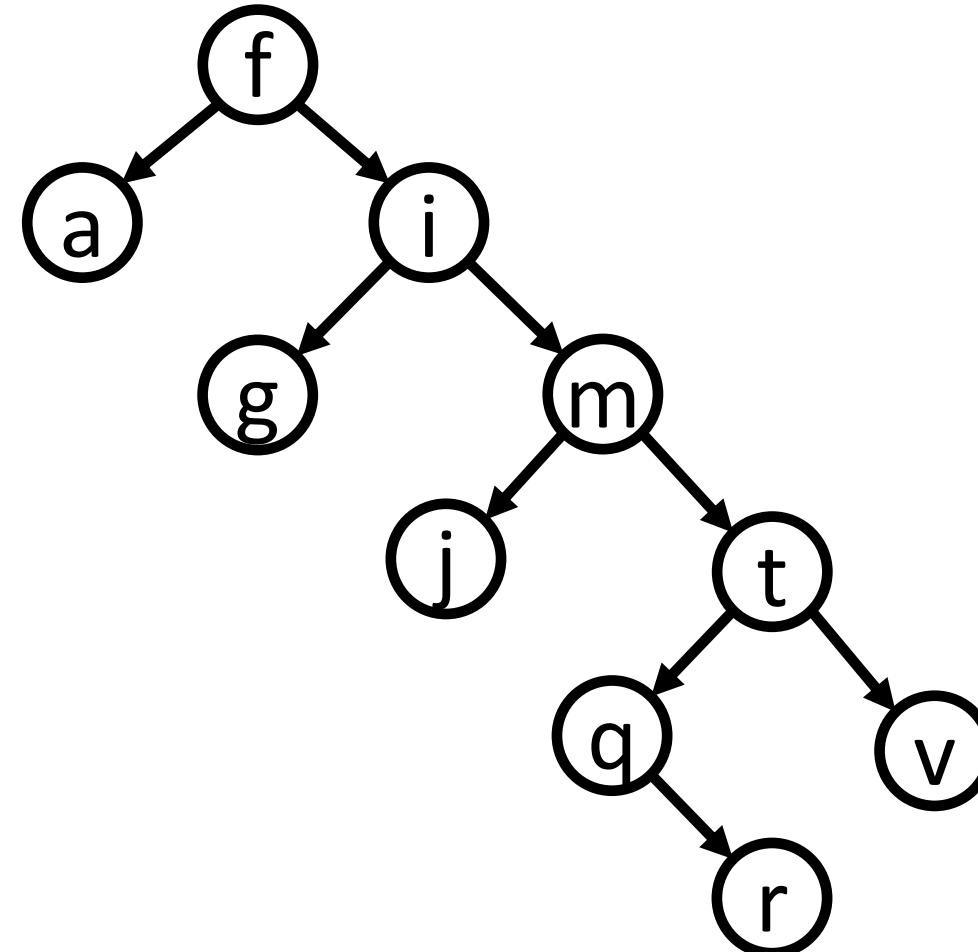
# Example: Insert



# Example: Insert

Zag-zig

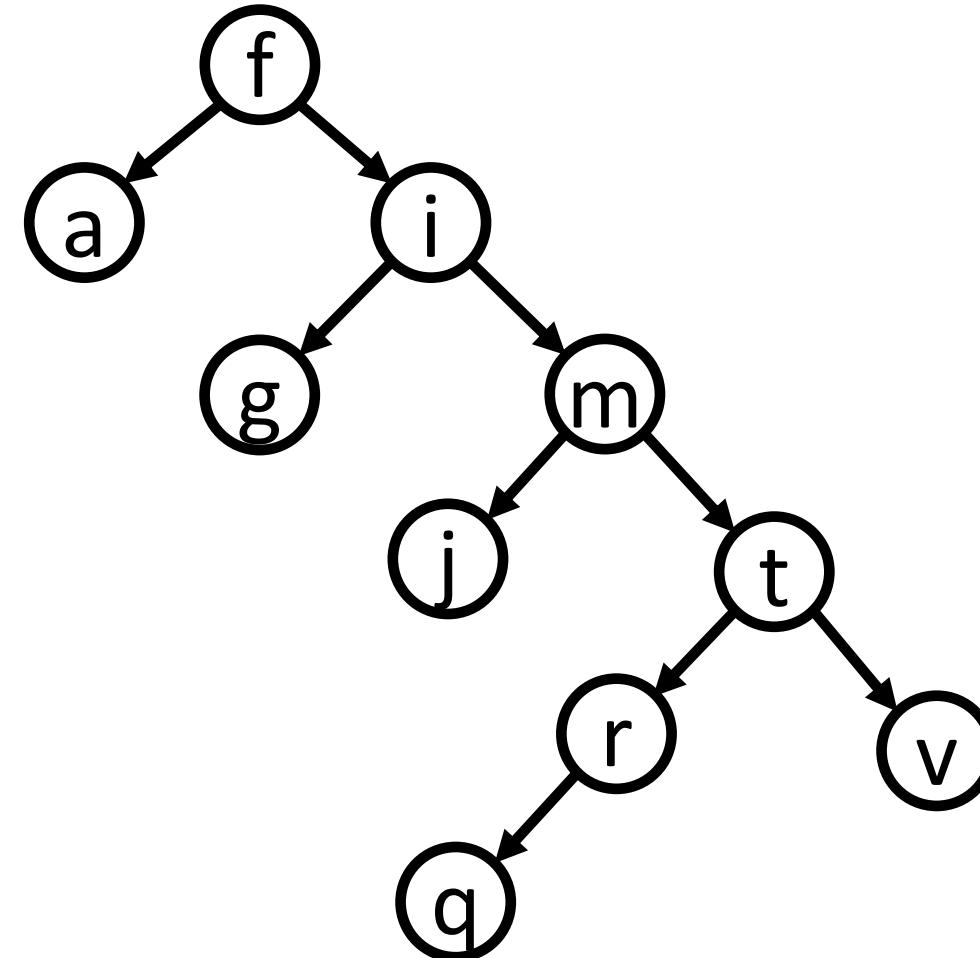
1. Rotate on parent
2. Rotate on new parent



# Example: Insert

Zag-zig

1. ~~Rotate on parent~~
2. Rotate on new parent



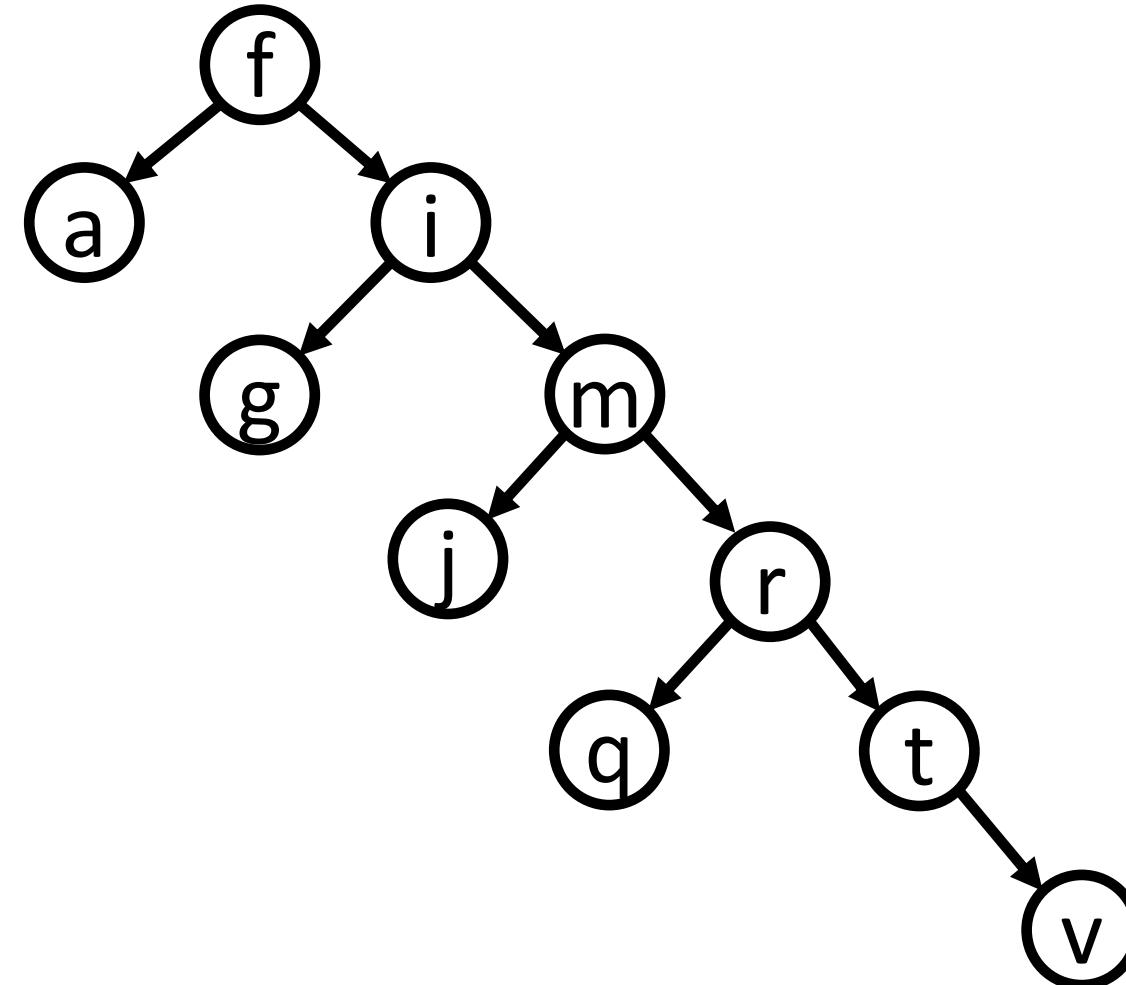
# Example: Insert

Zag-zig

1. ~~Rotate on parent~~
2. ~~Rotate on new parent~~

Zag-zag

1. ~~Rotate on grandparent~~
2. ~~Rotate on parent~~



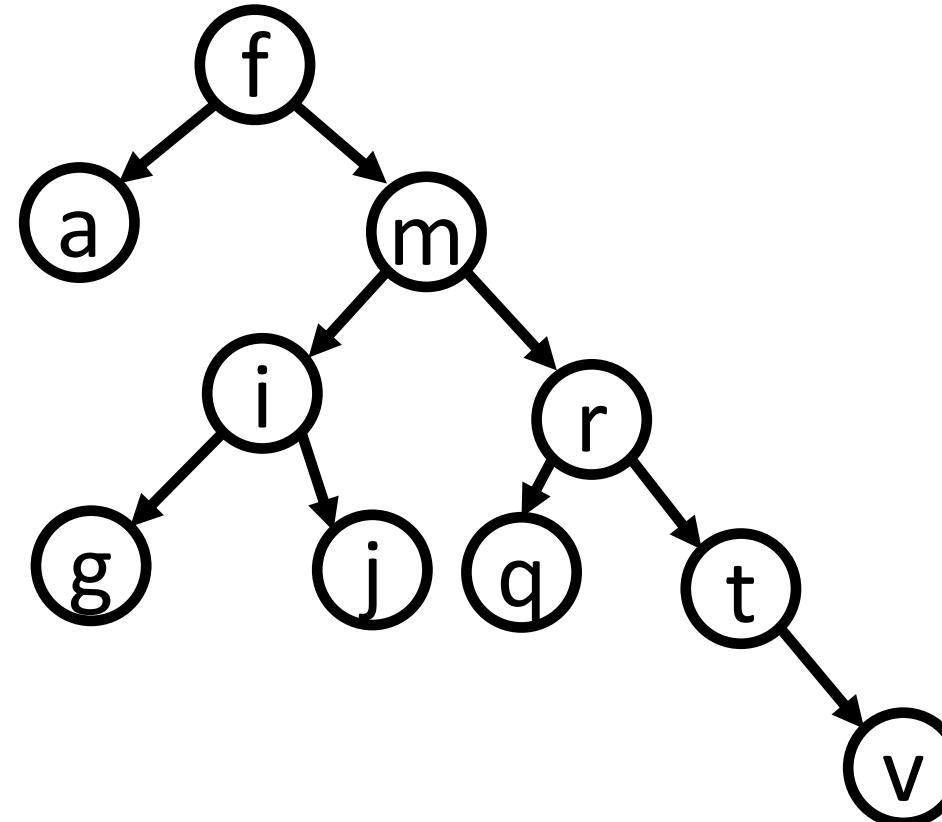
# Example: Insert

Zag-zig

1. ~~Rotate on parent~~
2. ~~Rotate on new parent~~

Zag-zag

1. ~~Rotate on grandparent~~
2. Rotate on parent



# Example: Insert

Zag-zig

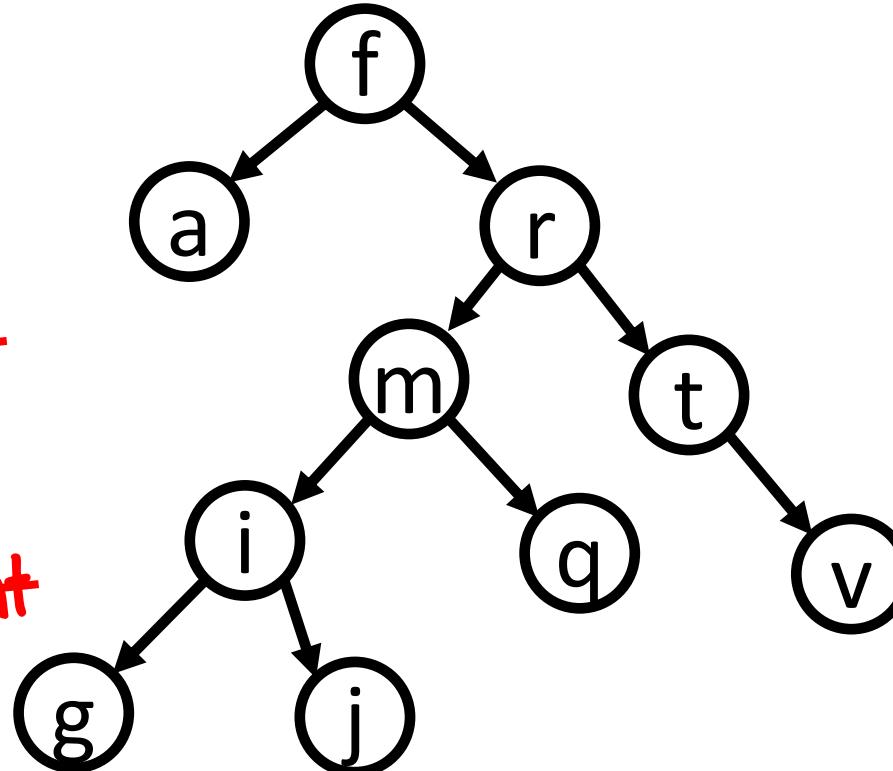
1. ~~Rotate on parent~~
2. ~~Rotate on new parent~~

Zag-zag

1. ~~Rotate on grandparent~~
2. ~~Rotate on parent~~

Zag

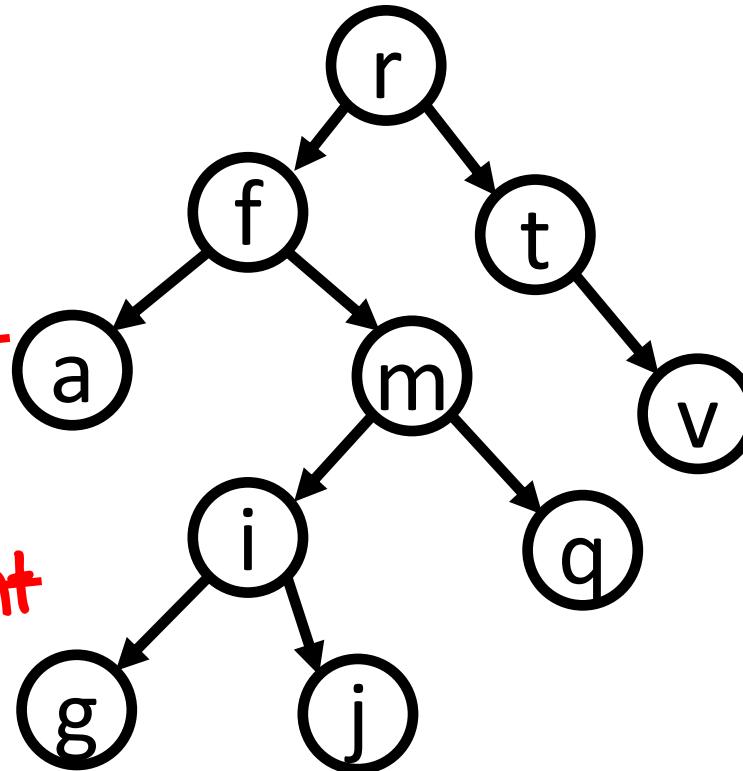
1. ~~Rotate on parent~~



# Example: Insert

Zag-zig

1. ~~Rotate on parent~~
2. ~~Rotate on new parent~~



Zag-zag

1. ~~Rotate on grandparent~~
2. ~~Rotate on parent~~

Zag

1. ~~Rotate on parent~~

# Summary

- Splay Operation
  - Move the given node to the root
  - Use zig-zig and zag-zag rotations when possible
- Insert
  - Insert as usual
  - Splay new node
- Search
  - Search as usual
  - Splay found node

Coming Up...

Quinn Returns!

# Banker's Method: Intro

# Recall: Array-Backed List

- Amortized  $O(1)$  append
- How did we prove it?
  - Analyzed worst-case complexity of  $m$  appends
  - Divided by  $m$  to find time per operation

# Proving Amortized Bounds

- Aggregate Method
  - Analyze worst-case complexity of  $m$  operations
  - Divide by  $m$  for get time per operation
- Limitations
  - What if appending and popping in an array-backed list?
  - What if inserting and searching in a splay tree?
  - Hard to analyze every possible sequence of operations.

# Proving Amortized Bounds

- Aggregate Method
  - Analyze worst-case complexity of  $m$  operations
  - Divide by  $m$  for get time per operation
- Banker's Method (Accounting Method)
  - Treat time like money – allowed to save it for later
  - “Overcharge” for cheap operations, and save the extra
  - Show that there is always enough “in the bank” to pay for expensive operations
- Physicist's Method (Potential Method)
  - Maybe when you're older...

# Revenge of the Train: The Quinnening

- The train is just like an array-backed list!
- Each constant-time step costs 1 coin
  - “Loading” a “box” (putting an item in the array)
  - “Moving” a “box” (copying an item to the new array)
- How much should Quinn charge each “customer” (call to append)?
  - 1 coin per append
    - Pays for loading the box, but not for copying it
  - 2 coins per append
    - Pays for loading the box and copying the first time, but not the second time!
  - 3 coins per append
    - Seems to be enough...

# Summary

- Aggregate method
  - Analyze sequence of operations
  - Find per-operation time
- Not always easy when there are many possible sequences
- Banker's method
  - “Overcharge” for cheap operations, save the extra
  - Show that there is always enough “money” for expensive operations
- Train example
  - Charging 3 coins per append seems to be enough
  - Constant price means amortized  $O(1)$  time!

# Coming Up...

Proving that 3 coins per append is enough

# Banker's Method: Details

# Recall: Proving Amortized Bounds

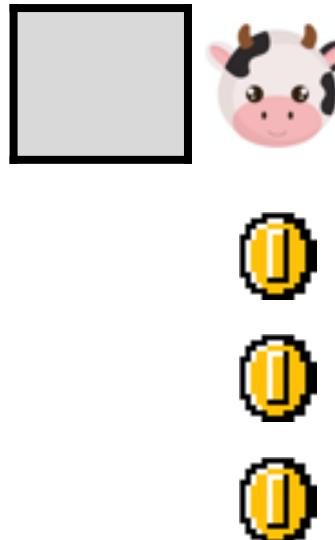
- Aggregate Method
  - Analyze worst-case complexity of  $m$  operations
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  - Maybe when you're older...

# Banker's Method: Append/Expansion

- Show that charging 3 “coins” per append is enough

Paying for operations on item  $i$ :

- “Load”
  - Use first coin



# Banker's Method: Append/Expansion

- Show that charging 3 “coins” per append is enough

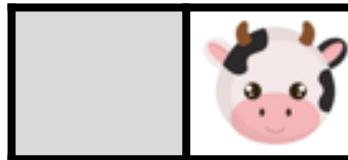


Paying for operations on item  $i$ :

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# Banker's Method: Append/Expansion

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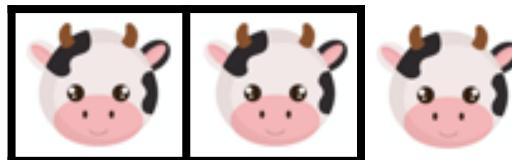


Paying for operations on item  $i$ :

- “Load”
  - Use first coin
- 1<sup>st</sup> “Move”
  - Use second coin

# Banker's Method: Append/Expansion

- Show that charging 3 “coins” per append is enough

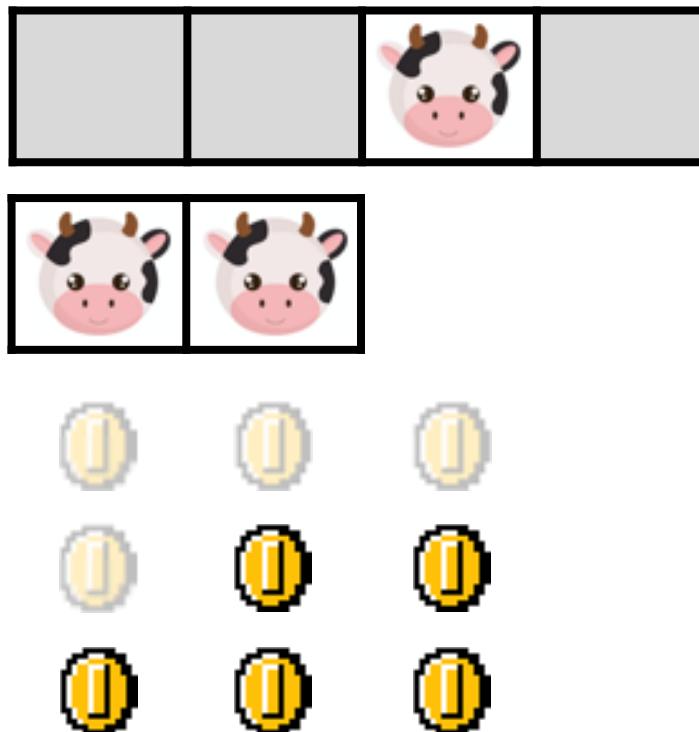


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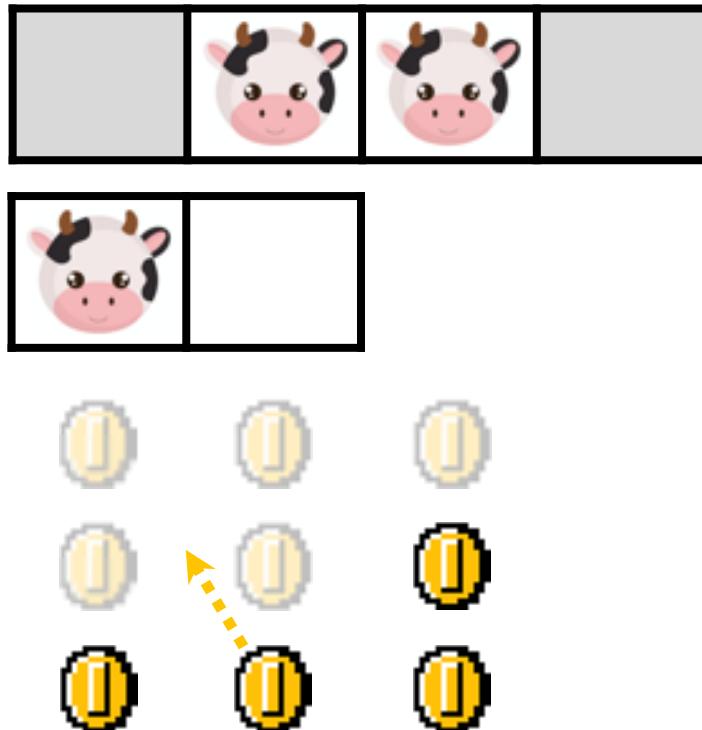


Paying for operations on item  $i$ :

- “Load”
  - Use first coin
- 1<sup>st</sup> “Move”
  - Use second coin

# Banker's Method: Append/Expansion

- Show that charging 3 “coins” per append is enough

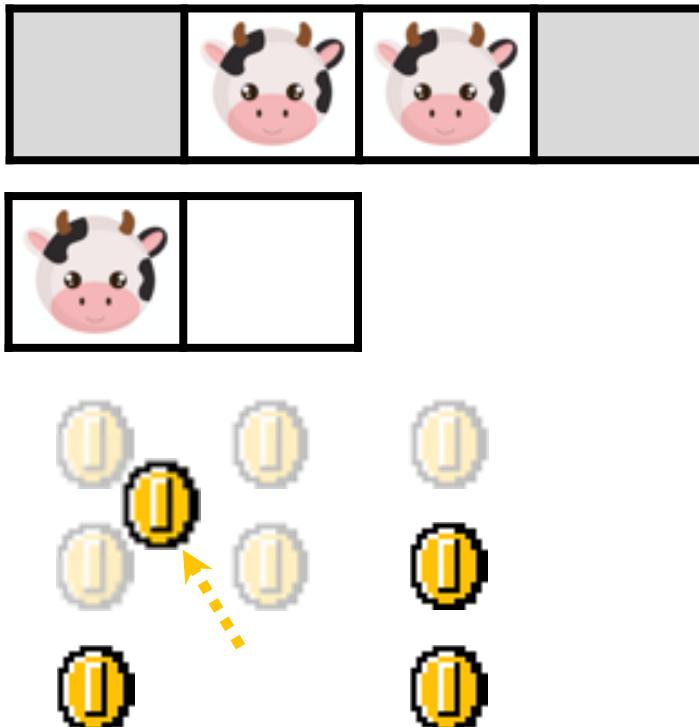


Paying for operations on item  $i$ :

- “Load”
  - Use first coin
- 1<sup>st</sup> “Move”
  - Use second coin

# Banker's Method: Append/Expansion

- Show that charging 3 “coins” per append is enough



Paying for operations on item  $i$ :

- “Load”
  - Use first coin
- 1<sup>st</sup> “Move”
  - Use second coin
- All other “Moves”
  - Use third coin from item  $n/2 + i$

This coin has been deposited  
because  $n/2$  items have been  
appended since last resize!

# Banker's Method: Append/Expansion

- Show that charging 3 “coins” per append is enough

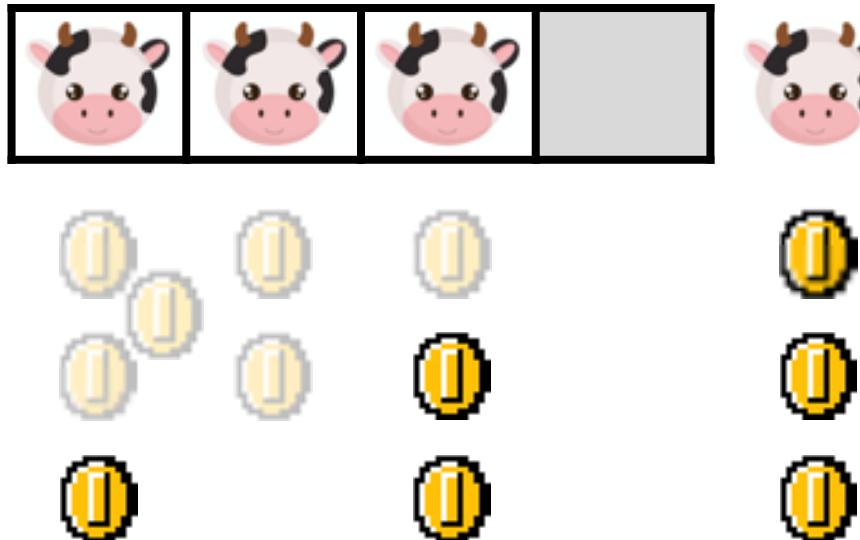


Paying for operations on item  $i$ :

- “Load”
  - Use first coin
- 1<sup>st</sup> “Move”
  - Use second coin
- All other “Moves”
  - Use third coin from item  $n/2 + i$

# Banker's Method: Append/Expansion

- Show that charging 3 “coins” per append is enough

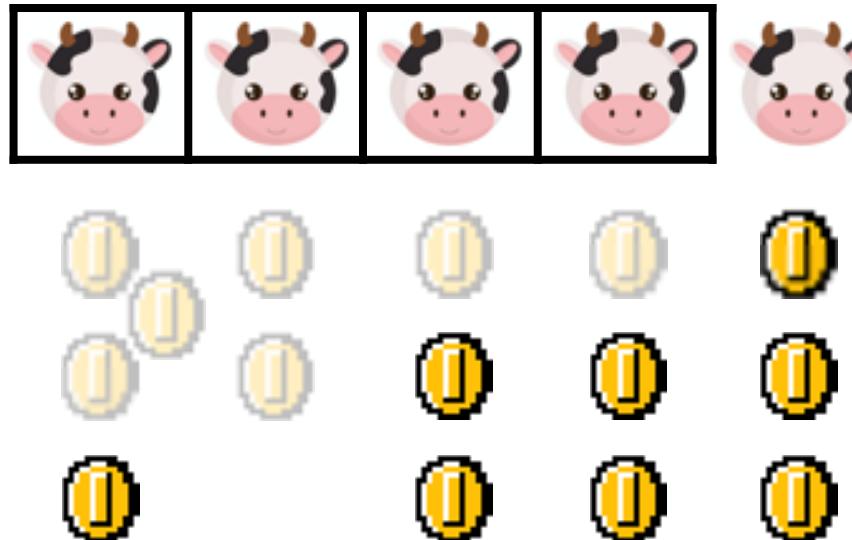


Paying for operations on item  $i$ :

- “Load”
  - Use first coin
- 1<sup>st</sup> “Move”
  - Use second coin
- All other “Moves”
  - Use third coin from item  $n/2 + i$

# Banker's Method: Append/Expansion

- Show that charging 3 “coins” per append is enough

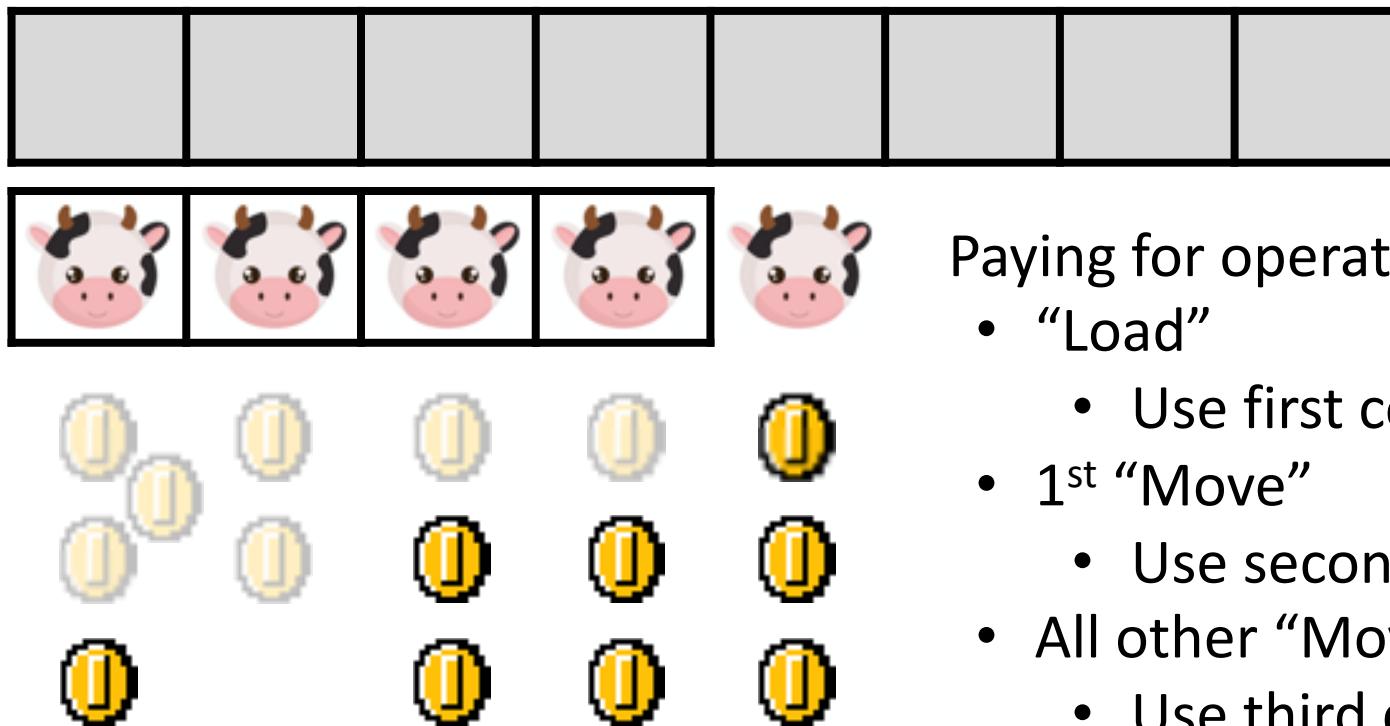


Paying for operations on item  $i$ :

- “Load”
  - Use first coin
- 1<sup>st</sup> “Move”
  - Use second coin
- All other “Moves”
  - Use third coin from item  $n/2 + i$

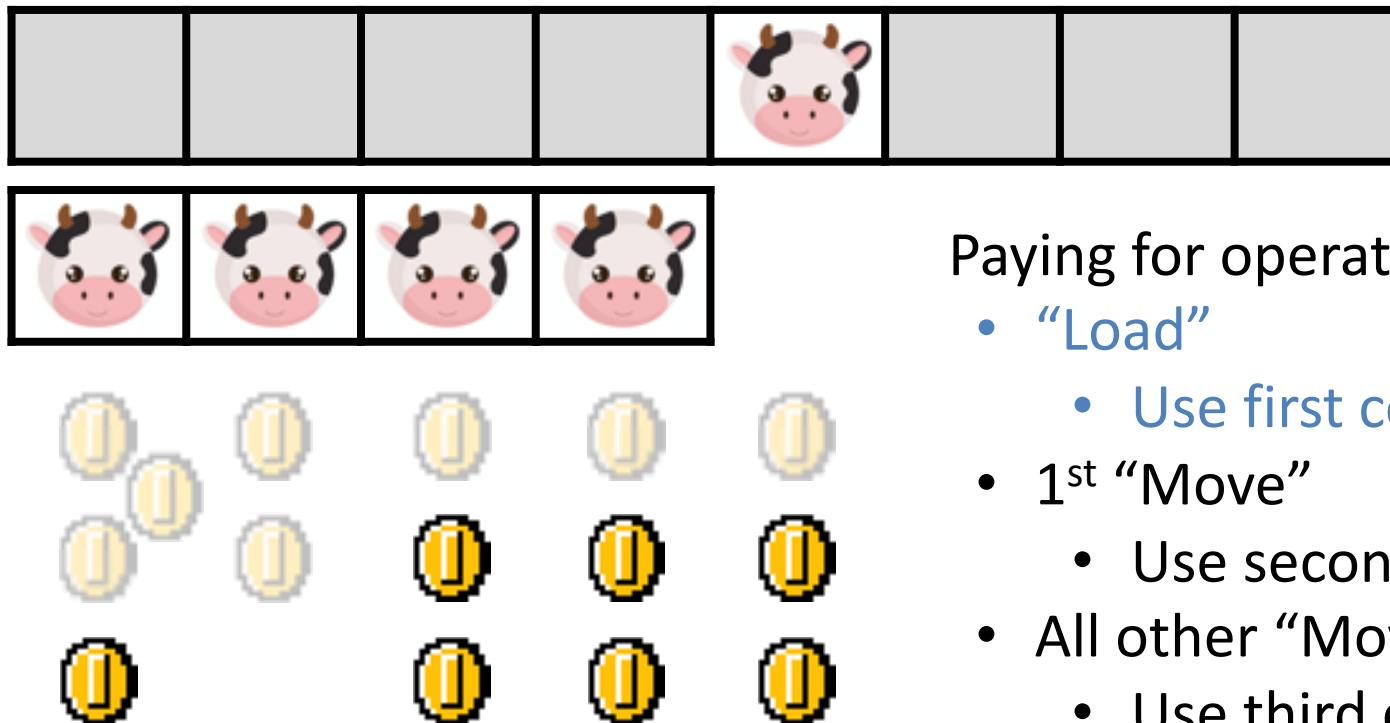
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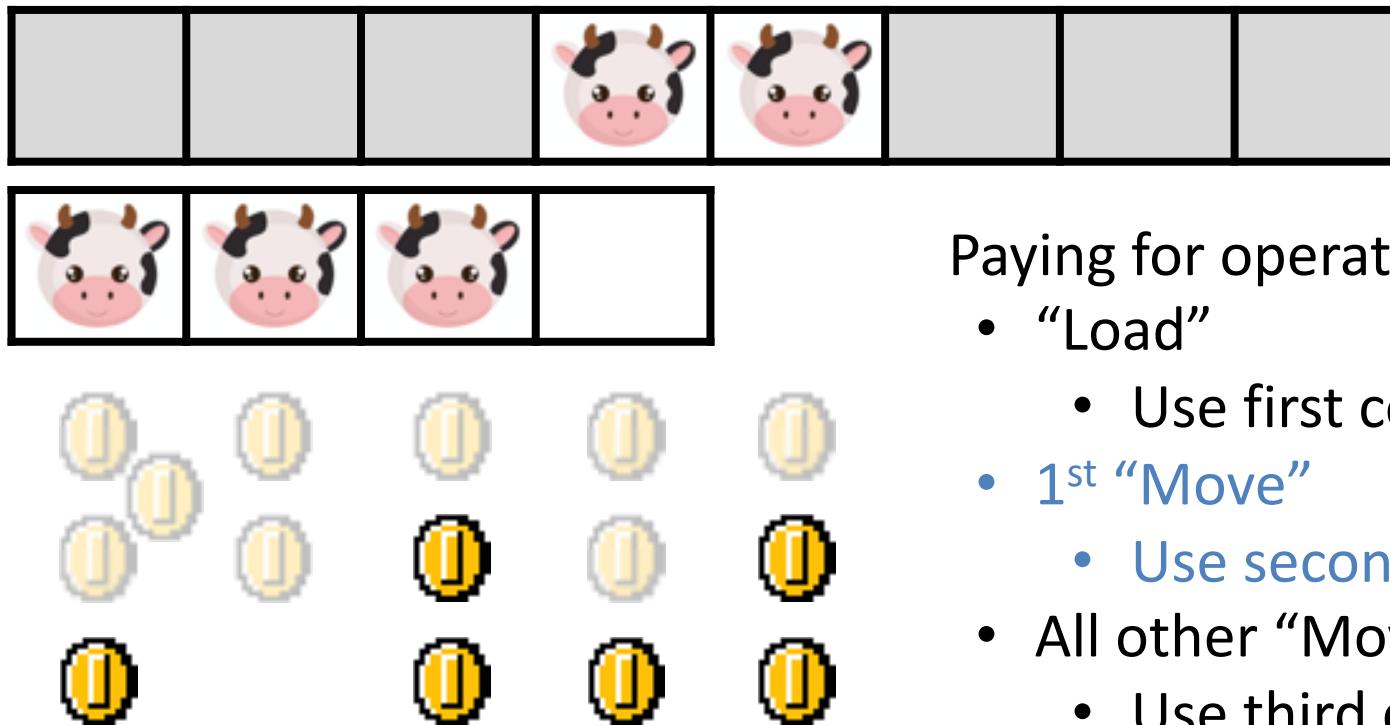
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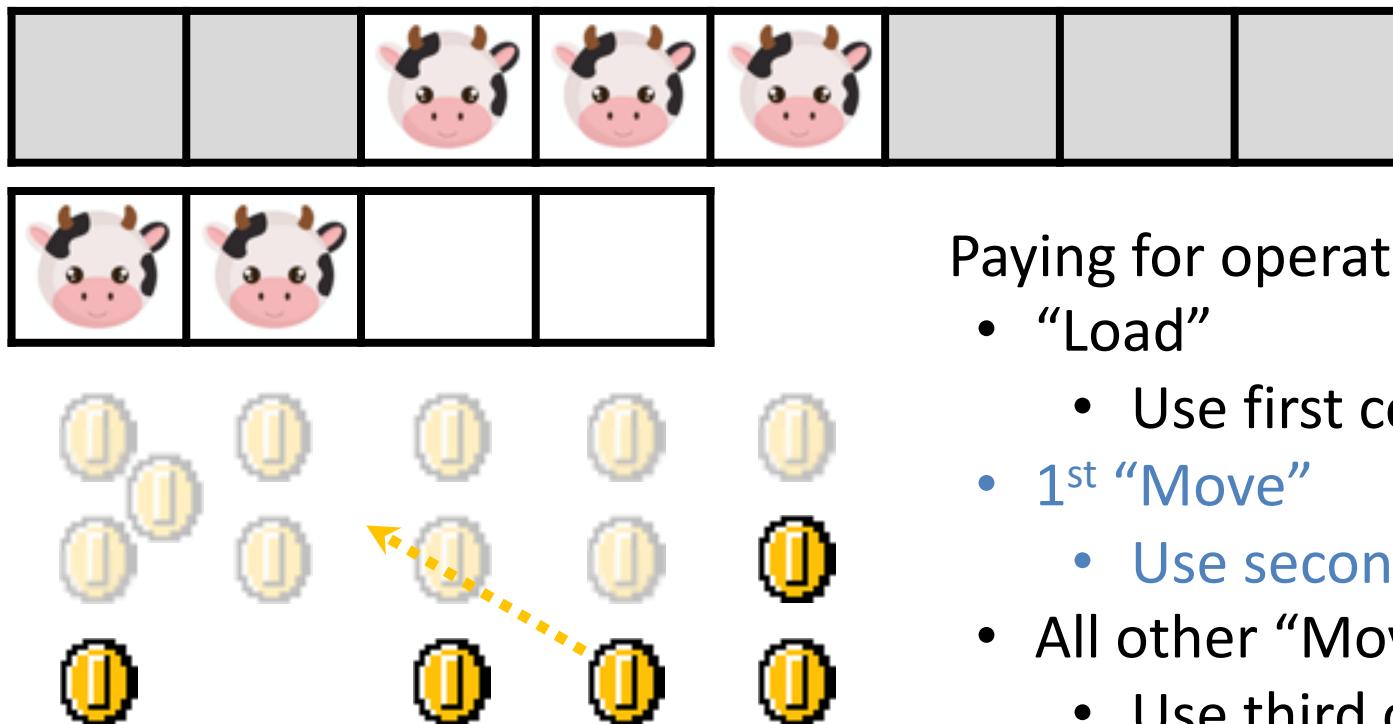
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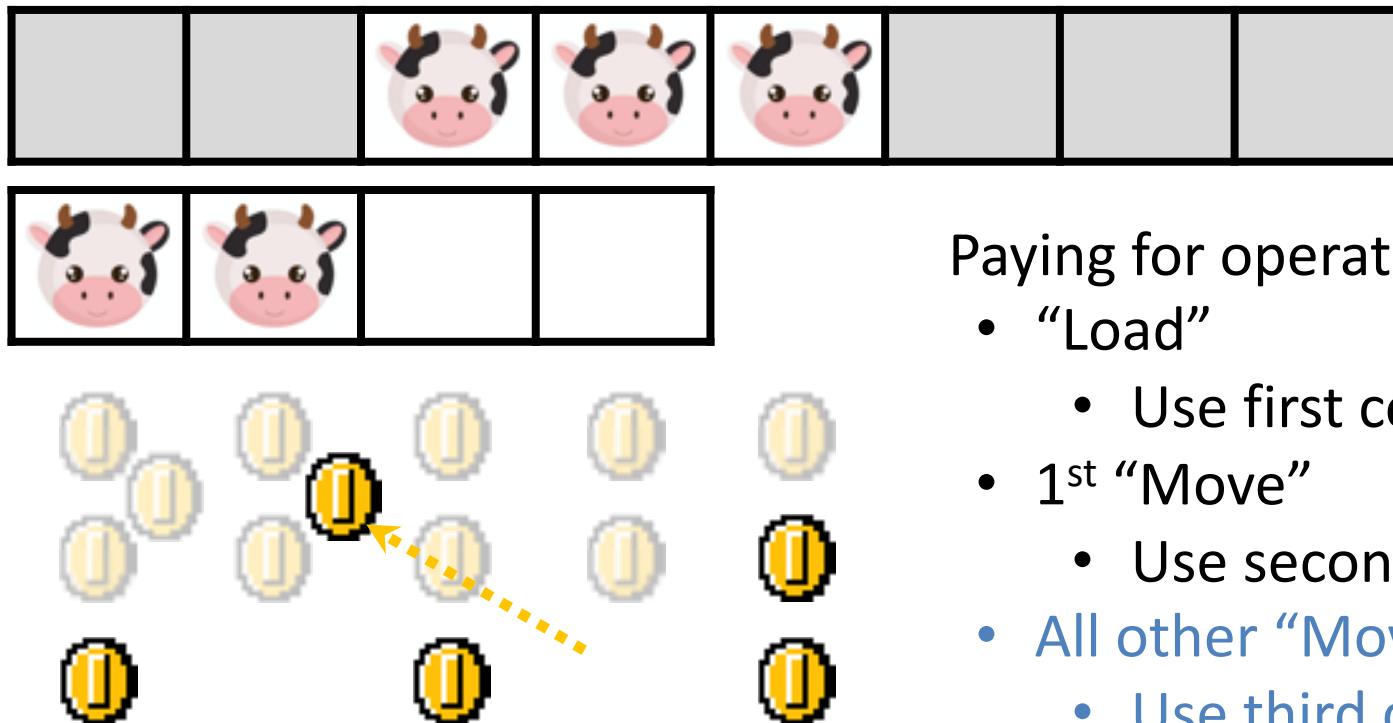
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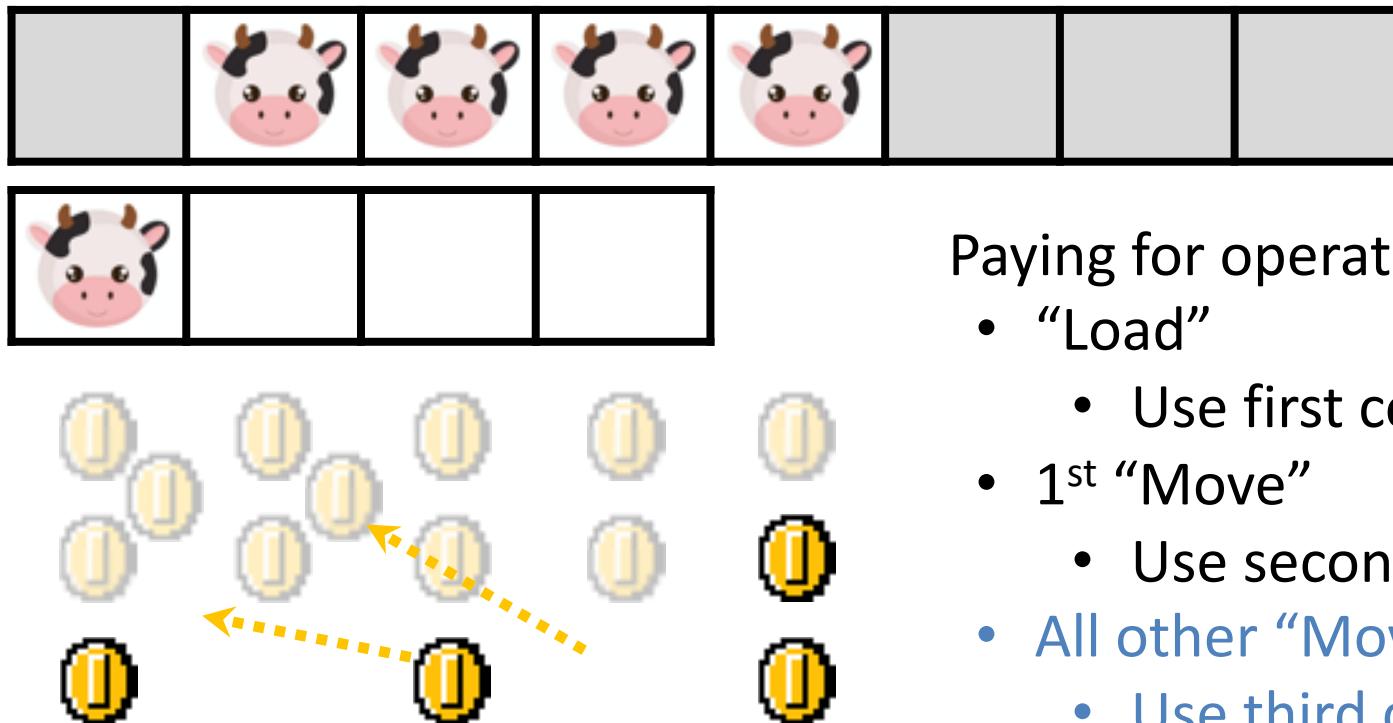
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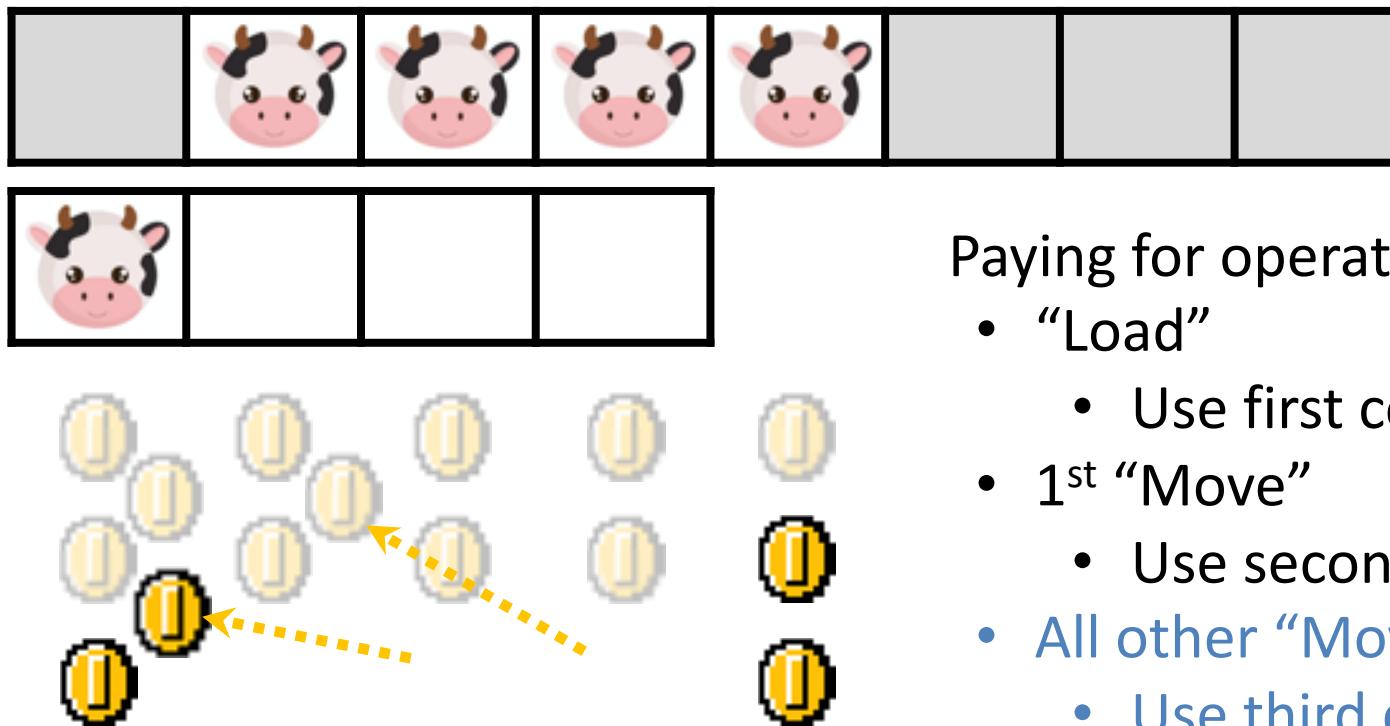
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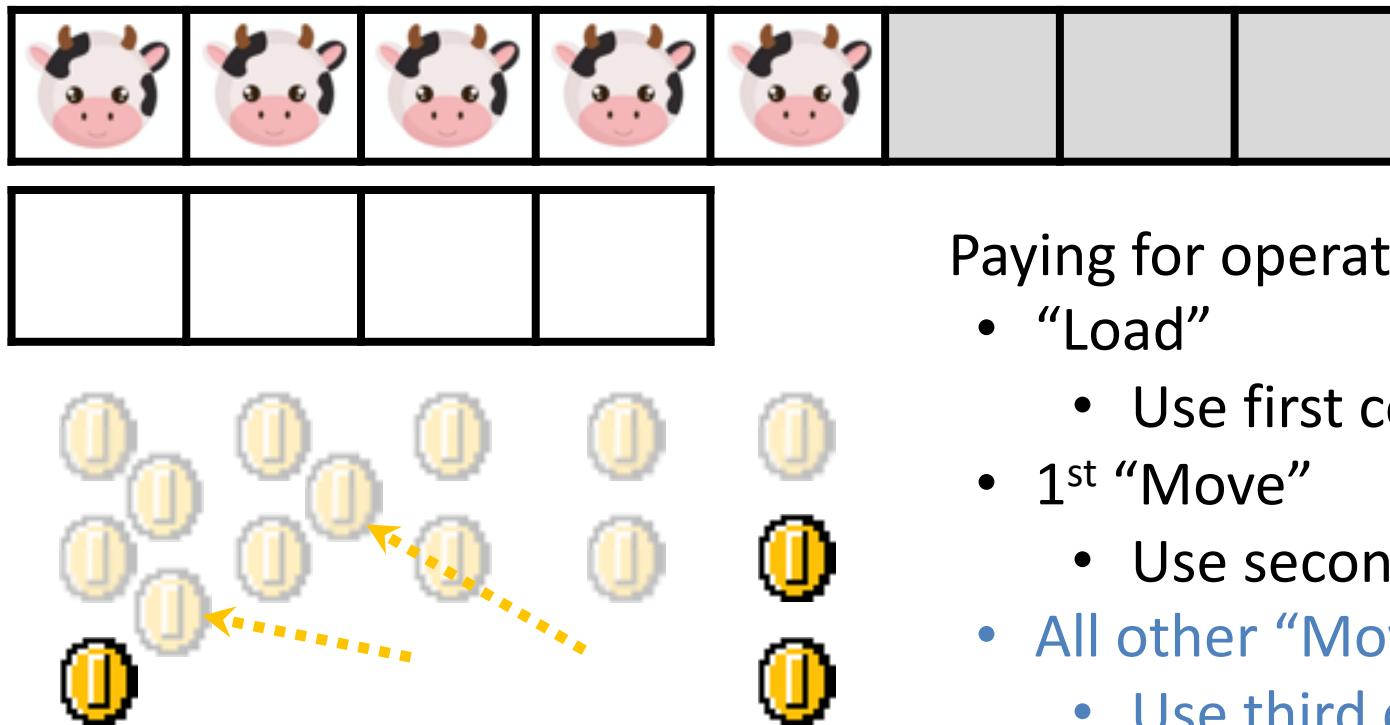
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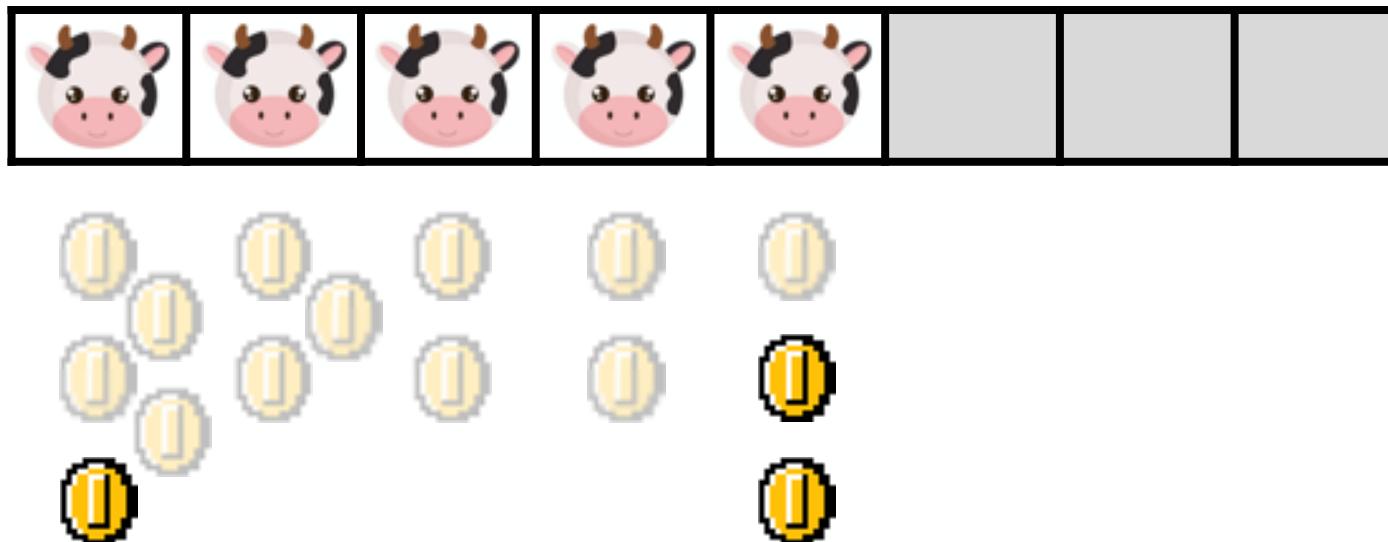
# Banker's Method: Append/Expansion

- Show that charging 3 “coins” per append is enough



# Banker's Method: Append/Expansion

- Show that charging 3 “coins” per append is enough
  - Since we can always pay for loading and moving each item, 3 “coins” is enough
  - Since we can charge a constant price for each append, append has amortized  $O(1)$  complexity



# Banker's Method: Pop/Shrink

- What about popping from the back, and shrinking the array?
  - Recall: we shrink when  $\text{size} = \text{capacity}/4$
- How much should we charge for a pop operation?
  - Charge 2 coins for each pop
  - Paying for operations
    - Remove last item: use the first coin from the pop
    - Copy item  $i$  to smaller array: use the second coin from popping item  $n + i$
  - Why can we guarantee that the copy coin has been deposited?
    - When there have been no pops since last resize,  $\text{size} \geq \text{capacity}/2$
    - So when we shrink, we must have popped at least half of the items since the last resize
    - If size at shrinking is  $n$ , then we have popped at least  $n$  items.
  - Since we can charge  $O(1)$  coins, pop has  $O(1)$  amortized time

# Splay Trees?

- High-level:
  - For each splay (insert/search) charge a price that is logarithmic in  $n$
  - Show that you can always pay for every step of a splay operation
- We won't go through the argument in CS70
  - But you can find it online
  - (e.g. <https://www.cs.cmu.edu/~rmarko/lec04.pdf>)



# Summary

- Using the Banker’s method
  - Set a “price” for each operation
    - The price may depend on  $n$ !
  - Show how to pay for each  $O(1)$  step
    - Typically using “coins” saved up from earlier operations
    - The price gives the amortized time for each operation
    - The operations can be interleaved in any sequence because they are “paid for”!
- Array-backed lists
  - Append and pop (from back) both have amortized  $O(1)$  complexity
- Splay trees
  - Insert and search both have amortized  $O(\log n)$  complexity