

9 Union Find

Union Find Data Structure \mathcal{P} : Maintains a partition of **disjoint** sets over elements.

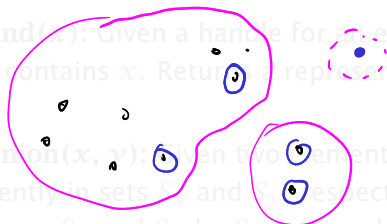
- ▶ \mathcal{P} . **makeset**(x): Given an element x , adds x to the data structure and creates a singleton set that contains only this element. Returns a locator/handle for x in the data structure.
- ▶ \mathcal{P} . **find**(x): Given a handle for an element x ; find the set that contains x . Returns a representative/identifier for this set.
- ▶ \mathcal{P} . **union**(x, y): Given two elements x , and y that are currently in sets S_x and S_y , respectively, the function replaces S_x and S_y by $S_x \cup S_y$ and returns an identifier for the new set.



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Applications:

- ▶ Keep track of the connected components of a dynamic graph that changes due to insertion of nodes and edges.
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Algorithm 16 Kruskal-MST($G = (V, E), w$)

1: $A \leftarrow \emptyset$;

2: **for all** $v \in V$ **do**

3: $v.\text{set} \leftarrow \mathcal{P}.\text{makeset}(v.\text{label})$ (h)

4: sort edges in non-decreasing order of weight w

5: **for all** $(u, v) \in E$ in non-decreasing order **do**

6: **if** $\mathcal{P}.\text{find}(u.\text{set}) \neq \mathcal{P}.\text{find}(v.\text{set})$ **then** $|E| = m$

7: $\rightarrow A \leftarrow A \cup \{(u, v)\}$ $\leftarrow n-1$

8: $\mathcal{P}.\text{union}(u.\text{set}, v.\text{set}) \leftarrow n-1$

List Implementation

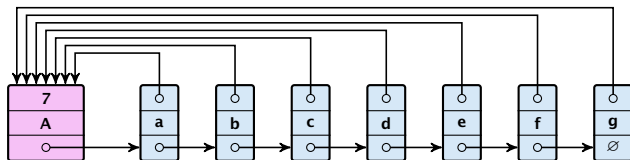
- ▶ The elements of a set are stored in a list; each node has a backward pointer to the head.
- ▶ The head of the list contains the identifier for the set and a field that stores the size of the set.



- ▶ `makeset(x)` can be performed in constant time.
- ▶ `find(x)` can be performed in constant time.

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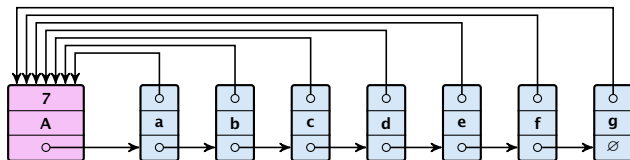
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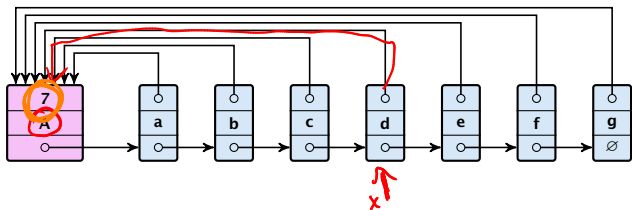
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union(x, y)

- ▶ Determine sets S_x and S_y .
- ▶ Traverse the smaller list (say S_y), and change all backward pointers to the head of list S_x .
- ▶ Insert list S_y at the head of S_x .
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- ▶ Time: $\min\{|S_x|, |S_y|\}$.

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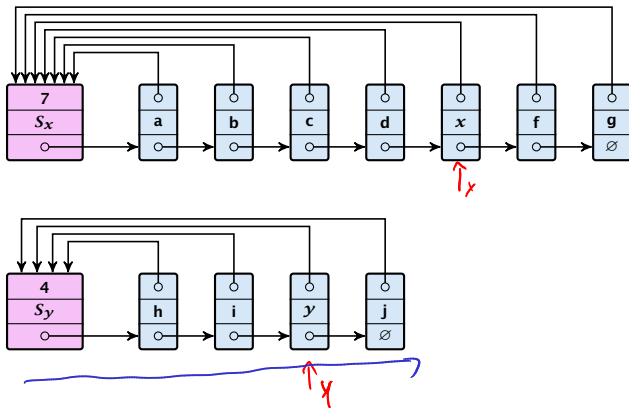
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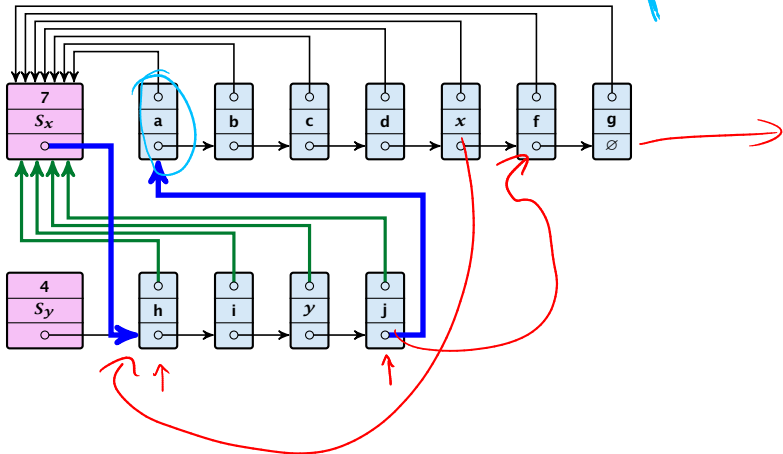
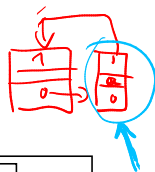
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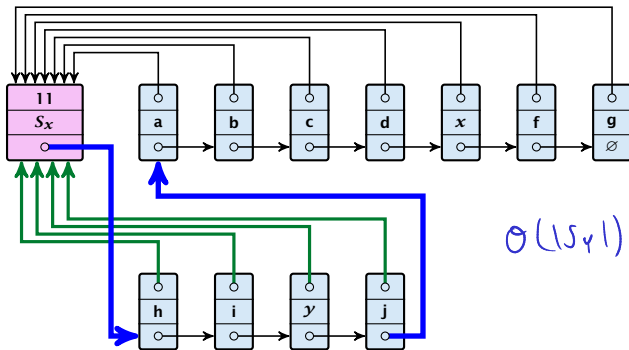
List Implementation

makeSet()

makeSet(~~0~~)



List Implementation



List Implementation

$$n + 2|E| + (n-1) \mathcal{O}(n)$$

Running times:

- ▶ $\text{find}(x)$: constant
- ▶ $\text{makeset}(x)$: constant
- ▶ $\text{union}(x, y)$: $\mathcal{O}(n)$, where n denotes the number of elements contained in the set system.

List Implementation

Lemma 34

The list implementation for the ADT union find fulfills the following amortized time bounds:

- $\mathcal{O}(1)$ ▶ $\text{find}(x): \mathcal{O}(1)$.
- $\mathcal{O}(1)$ ▶ $\text{makeset}(x): \mathcal{O}(\log n)$.
- $\mathcal{O}(n)$ ▶ $\text{union}(x, y): \mathcal{O}(1)$.

The Accounting Method for Amortized Time Bounds

- ▶ There is a bank account for every element in the data structure.
- ▶ Initially the balance on all accounts is zero.
- ▶ Whenever for an operation the amortized time bound exceeds the actual cost, the difference is credited to some bank accounts of elements involved.
- ▶ Whenever for an operation the actual cost exceeds the amortized time bound, the difference is charged to bank accounts of some of the elements involved.
- ▶ If we can find a charging scheme that guarantees that balances always stay positive the amortized time bounds are proven.

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List Implementation

- ▶ For an operation whose actual cost exceeds the amortized cost we charge the **excess** to the elements involved.
- ▶ In total we will charge at most $\mathcal{O}(\log n)$ to an element (regardless of the request sequence).
- ▶ For each element a makeset operation occurs as the first operation involving this element.
- ▶ We inflate the amortized cost of the makeset-operation to $\Theta(\log n)$, i.e., at this point we fill the bank account of the element to $\Theta(\log n)$.
- ▶ Later operations charge the account but the balance never drops below zero.

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makeSet(x): The actual cost is $\mathcal{O}(1)$. Due to the cost inflation the amortized cost is $\mathcal{O}(\log n)$.

find(x): For this operation we define the amortized cost and the actual cost to be the same. Hence, this operation does not change any accounts. Cost: $\mathcal{O}(1)$.

union(x, y):

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Lemma 35

An element is charged at most $\lfloor \log_2 n \rfloor$ times, where n is the total number of elements in the set system.

Proof.

Whenever an element x is charged the number of elements in x 's set doubles. This can happen at most $\lfloor \log n \rfloor$ times. \square

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Implementation via Trees

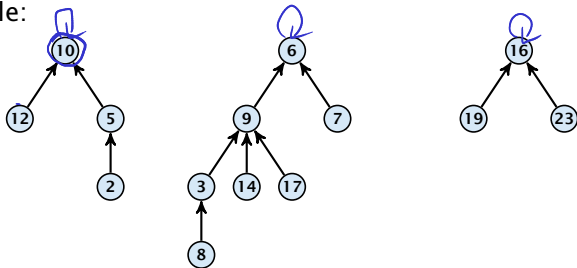
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- ▶ The root of the tree is the label of the set.
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- ▶ Example:



Set system $\{2, 5, 10, 12\}, \{3, 6, 7, 8, 9, 14, 17\}, \{16, 19, 23\}$.

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- ▶ Create a singleton tree. Return pointer to the root.
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find(x)

Start at element x in the tree, and repeatedly update x to be its parent until it reaches the root.

The root is the element x such that $\text{parent}(x) = x$.

Time complexity: $\mathcal{O}(h)$, where h is the height of the tree.

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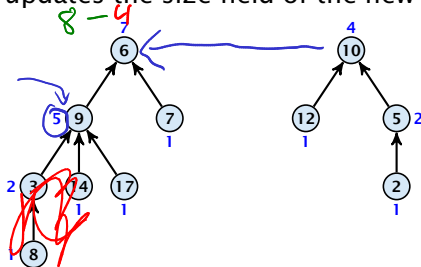
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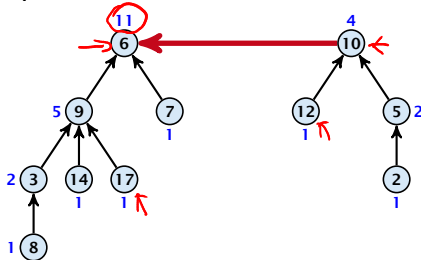


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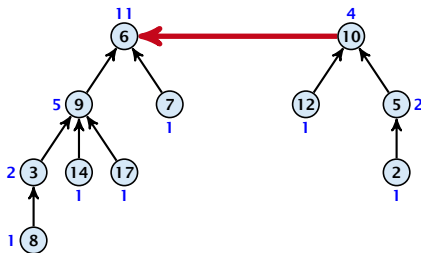


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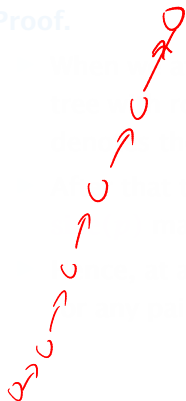
- ▶ Time: constant for $\text{link}(a, b)$ plus two find-operations.

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The running time (non-amortized!!!) for $\text{find}(x)$ is $\mathcal{O}(\log n)$.

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- ▶ After that the value of $\text{size}(c)$ stays fixed, while the value of $\text{size}(p)$ may still increase.
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- ▶ After that the value of $\text{size}(c)$ stays fixed, while the value of $\text{size}(p)$ may still increase.
- ▶ Hence, at any point in time a tree fulfills $\text{size}(p) \geq 2 \text{size}(c)$, for any pair of nodes (p, c) , where p is a parent of c .



Path Compression

find(x):

- ▶ Go upward until you find the root.
- ▶ Re-attach all visited nodes as children of the root.
- ▶ Speeds up successive find-operations.



Now that there is only one root, how many nodes are in the same set?

9 (all 9 nodes)

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Path Compression

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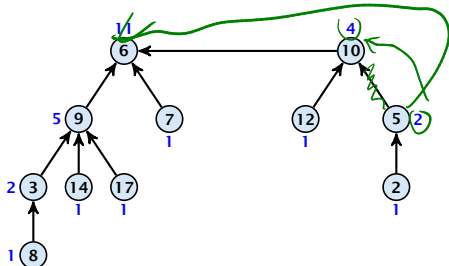
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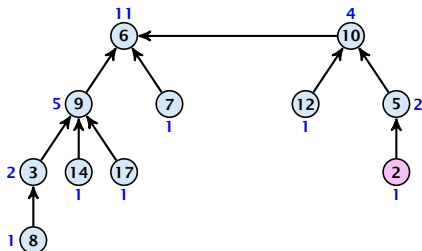


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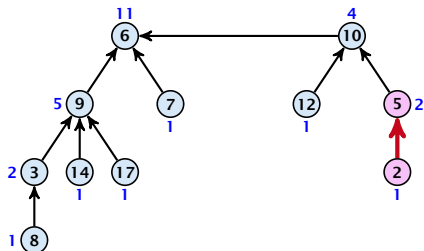


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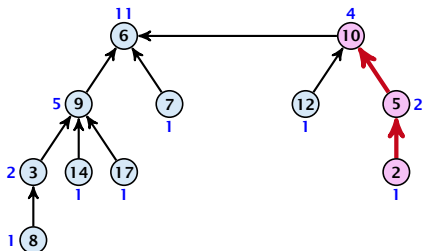


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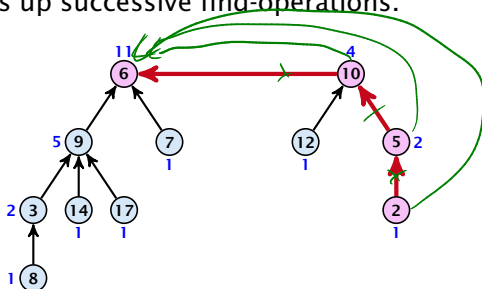


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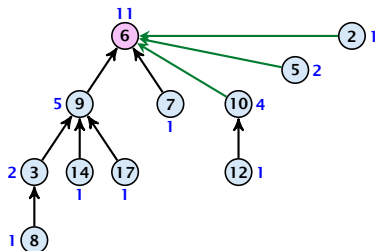


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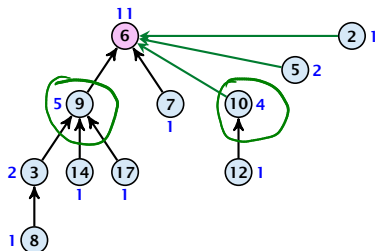


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Path Compression

Asymptotically the cost for a find-operation does not increase due to the path compression heuristic.

However, for a worst-case analysis there is no improvement on the running time. It can still happen that a find-operation takes time $\mathcal{O}(\log n)$.

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Amortized Analysis

Definitions:

Rank of a node w : the number of nodes that were in the subtree rooted at w when w became the child of another node (or the number of nodes if w is the root).

Rank of a node is the same as the size of its subtree in the case that there are no find-operations.

Lemma 37

The rank of a parent must be strictly larger than the rank of a child.

Amortized Analysis

Definitions:

- ▶ $\text{size}(v)$:= the number of nodes that were in the sub-tree rooted at v when v became the child of another node (or the number of nodes if v is the root).

Note that this is the same as the size of v 's subtree in the case that there are no find-operations.

- ▶ $\text{rank}(v) = \lfloor \log(\text{size}(v)) \rfloor$.
- ▶ $\Rightarrow \text{size}(v) \geq 2^{\text{rank}(v)}$.

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Amortized Analysis

Lemma 38

There are at most $n/2^s$ nodes of rank s .

Proof.

Let S be a node of rank s . Then S has at least 2^{s-1} children. The total number of nodes of rank $s-1$ is at most $n/2^{s-1}$. Thus, there are at most $n/2^{s-1} / 2^{s-1} = n/2^s$ nodes of rank s . This is the claim. \square

Amortized Analysis

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There are at most $n/2^s$ nodes of rank s .

Proof.

- ▶ Let's say a node v sees node x if v is in x 's sub-tree at the time that x becomes a child.
- ▶ A node v sees at most one node of rank s during the running time of the algorithm.
- ▶ This holds because the rank-sequence of the roots of the different trees that contain v during the running time of the algorithm is a strictly increasing sequence.
- ▶ Hence, every node sees at most one rank s node, but every rank s node is seen by at least 2^s different nodes. □

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We define

$$\text{tow}(i) := \begin{cases} 1 & \text{if } i = 0 \\ 2^{\text{tow}(i-1)} & \text{otw.} \end{cases}$$

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Theorem 39

Union find with path compression fulfills the following amortized running times:

- ▶ $\text{makeset}(x) : \mathcal{O}(\log^*(n))$
- ▶ $\text{find}(x) : \mathcal{O}(\log^*(n))$
- ▶ $\text{union}(x, y) : \mathcal{O}(\log^*(n))$

Amortized Analysis

In the following we assume $n \geq 2$.

rank-group:

A node with rank r has 2^r children in the next level.

The rank of a node is the number of nodes with rank $> r$.

rank group r contains 2^r nodes.

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In the following we assume $n \geq 2$.

rank-group:

- ▶ A node with rank $\text{rank}(v)$ is in **rank group** $\log^*(\text{rank}(v))$.
- ▶ The rank-group $g = 0$ contains only nodes with rank 0 or rank 1.
- ▶ A rank group $g \geq 1$ contains ranks $\text{tow}(g-1) + 1, \dots, \text{tow}(g)$.
- ▶ The maximum non-empty rank group is $\log^*(\lfloor \log n \rfloor) \leq \log^*(n) - 1$ (which holds for $n \geq 2$).
- ▶ Hence, the total number of rank-groups is at most $\log^* n$.

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Amortized Analysis

Accounting Scheme:

• Create an account for every find-operation

• Create an account for every node

The cost for a find-operation is equal to the length of the path traversed. We charge the cost for going from v to $\text{parent}[v]$ as follows:

• If v is the root we charge the cost to the account of v .

• Otherwise:

• If the grand-number of v is 0, then use as the account of v the account of $\text{parent}[v]$ (before storing path compression) we charge the cost to the node-account of $\text{parent}[v]$.

• Otherwise we charge the cost to the grand-number.

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- ▶ if v is the root we charge the cost to the account of the root
- ▶ if v is not the root we charge the cost to the account of $\text{parent}[v]$
- ▶ if the grand-father of v is the root we charge the cost to the account of the root
- ▶ if v is not the root and before starting path compression we charge the cost to the account of $\text{parent}[v]$
- ▶ if v is not the root and after path compression we charge the cost to the account of $\text{parent}[v]$

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The cost for a find-operation is equal to the length of the path traversed. We charge the cost for going from v to $\text{parent}[v]$ as follows:

- ▶ if the node v has a balance of 0, we charge the cost to the account of the find-operation.
- ▶ if the node v has a balance of $b > 0$, then we charge b to the account of the find-operation and we decrease the balance of v to 0.
- ▶ if the node v has a balance of $b < 0$, then we charge the cost to the account of the find-operation and we increase the balance of v to 0.

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- ▶ If $\text{parent}[v]$ is the root we charge the cost to the find-account.
- ▶ If the group-number of $\text{rank}(v)$ is the same as that of $\text{rank}(\text{parent}[v])$ (before starting path compression) we charge the cost to the node-account of v .
- ▶ Otherwise we charge the cost to the find-account.

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Amortized Analysis

Observations:

- The number of changed elements is bounded since for every element x we can only increase the rank of x at most $\log n$ times when increasing the number of elements in the set.
- The number of changed elements is bounded by $\log n$ by itself, the parent of x is x itself.
- The time charges to the parent will be in a separate rank group, and will never be charged again.
- The time charge made by a node in rank group i is at most

Amortized Analysis

Observations:

- ▶ A find-account is charged at most $\log^*(n)$ times (once for the root and at most $\log^*(n) - 1$ times when increasing the rank-group).
- ▶ After a node v is charged its parent-edge is re-assigned. The rank of the parent strictly increases.
- ▶ After some charges to v the parent will be in a larger rank-group. $\Rightarrow v$ will never be charged again.
- ▶ The total charge made to a node in rank-group g is at most $\text{tow}(g) - \text{tow}(g - 1) - 1 \leq \text{tow}(g)$.

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What is the total charge made to nodes?

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$$\sum_g n(g) \cdot \text{tow}(g),$$

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