Part I

Greedy Algorithms: Minimum Spanning Tree
Minimum Spanning Tree

Input  Connected graph $G = (V, E)$ with edge costs

Goal  Find $T \subseteq E$ such that $(V, T)$ is connected and total cost of all edges in $T$ is smallest

- $T$ is the minimum spanning tree (MST) of $G$
Minimum Spanning Tree

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Applications

- **Network Design**
  - Designing networks with minimum cost but maximum connectivity

- **Approximation algorithms**
  - Can be used to bound the optimality of algorithms to approximate Travelling Salesman Problem, Steiner Trees, etc.

- **Cluster Analysis**
Greedy Template

Initially \( E \) is the set of all edges in \( G \)
\( T \) is empty (* \( T \) will store edges of a MST *)
while \( E \) is not empty
    choose \( i \in E \)
    if (\( i \) satisfies condition)
        add \( i \) to \( T \)
return the set \( T \)

**Main Task:** In what order should edges be processed? When should we add edge to spanning tree?
Kruskal’s Algorithm

Process edges in the order of their costs (starting from the least) and add edges to $T$ as long as they don’t form a cycle.

Figure: Graph $G$

Figure: MST of $G$
Kruskal’s Algorithm

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Figure: Graph $G$

Figure: MST of $G$
Prim’s Algorithm

$T$ maintained by algorithm will be a tree. Start with a node in $T$. In each iteration, pick edge with least attachment cost to $T$.

Figure: Graph $G$

Figure: MST of $G$
**Prim’s Algorithm**

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Prim’s Algorithm

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![Graph G](image1)

![MST of G](image2)
Prim’s Algorithm

$T$ maintained by algorithm will be a tree. Start with a node in $T$. In each iteration, pick edge with least attachment cost to $T$.

Figure: Graph $G$

Figure: MST of $G$
Prim’s Algorithm

$T$ maintained by algorithm will be a tree. Start with a node in $T$. In each iteration, pick edge with least attachment cost to $T$.

Figure: Graph $G$

Figure: MST of $G$
Reverse Delete Algorithm

Initially $E$ is the set of all edges in $G$
$T$ is $E$ (* $T$ will store edges of a MST *)
while $E$ is not empty
    choose $i \in E$ of largest cost
    if removing $i$ does not disconnect $T$
        remove $i$ from $T$
return the set $T$

Returns a minimum spanning tree.
Correctness of MST Algorithms

- Many different MST algorithms
- All of them rely on some basic properties of MSTs, in particular the *Cut Property* to be seen shortly.
And for now . . .

Assumption

*Edge costs are distinct, that is no two edge costs are equal.*
Safe and Unsafe Edges

**Definition**

An edge $e = (u, v)$ is a **safe** edge if there is some partition of $V$ into $S$ and $V \setminus S$ and $e$ is the unique minimum cost edge crossing $S$ (one end in $S$ and the other in $V \setminus S$).
Safe and Unsafe Edges

Definition

An edge $e = (u, v)$ is a **safe** edge if there is some partition of $V$ into $S$ and $V \setminus S$ and $e$ is the unique minimum cost edge crossing $S$ (one end in $S$ and the other in $V \setminus S$).

Definition

An edge $e = (u, v)$ is an **unsafe** edge if there is some cycle $C$ such that $e$ is the unique maximum cost edge in $C$. 
Safe and Unsafe Edges

**Definition**
An edge $e = (u, v)$ is a **safe** edge if there is some partition of $V$ into $S$ and $V \setminus S$ and $e$ is the unique minimum cost edge crossing $S$ (one end in $S$ and the other in $V \setminus S$).

**Definition**
An edge $e = (u, v)$ is an **unsafe** edge if there is some cycle $C$ such that $e$ is the unique maximum cost edge in $C$.

**Proposition**
*If edge costs are distinct then every edge is either safe or unsafe.*

**Proof.**
Exercise.
Example

Figure: Graph with unique edge costs.
Figure: Graph with unique edge costs. Safe edges are red, rest are unsafe.
Key Observation: Cut Property

Lemma

If e is a safe edge then every minimum spanning tree contains e.
Key Observation: Cut Property

Lemma

*If* *e* is a safe edge *then every minimum spanning tree contains* *e*.

Proof.

*Suppose (for contradiction)* *e* is not in MST *T*. *Since* *e* is safe there is an *S* ⊂ V such that *e* is the unique min cost edge crossing *S*. *Since T is connected, there must be some edge* *f* with one end in *S* and the other in *V* \ *S*. *Since* *c* *f* > *c* *e*, *T*′ = (*T \ {f}* \ {e}) is a spanning tree of lower cost! *Error:* *T*′ may not be a spanning tree!!
Key Observation: Cut Property

**Lemma**

*If e is a safe edge then every minimum spanning tree contains e.*

**Proof.**

1. Suppose (for contradiction) e is not in MST $T$. 

Error: $T'$ may not be a spanning tree!
Key Observation: Cut Property

Lemma

If e is a safe edge then every minimum spanning tree contains e.

Proof.

- Suppose (for contradiction) e is not in MST T.
- Since e is safe there is an $S \subset V$ such that e is the unique min cost edge crossing S.
Key Observation: Cut Property

Lemma

If e is a safe edge then every minimum spanning tree contains e.

Proof.

- Suppose (for contradiction) e is not in MST T.
- Since e is safe there is an S ⊂ V such that e is the unique min cost edge crossing S.
- Since T is connected, there must be some edge f with one end in S and the other in V \ S
Key Observation: Cut Property

Lemma

If \( e \) is a safe edge then every minimum spanning tree contains \( e \).

Proof.

- Suppose (for contradiction) \( e \) is not in MST \( T \).
- Since \( e \) is safe there is an \( S \subset V \) such that \( e \) is the unique min cost edge crossing \( S \).
- Since \( T \) is connected, there must be some edge \( f \) with one end in \( S \) and the other in \( V \setminus S \).
- Since \( c_f > c_e \), \( T' = (T \setminus \{f\}) \cup \{e\} \) is a spanning tree of lower cost!
Key Observation: Cut Property

Lemma

If e is a safe edge then every minimum spanning tree contains e.

Proof.

- Suppose (for contradiction) e is not in MST $T$.
- Since e is safe there is an $S \subseteq V$ such that e is the unique min cost edge crossing $S$.
- Since $T$ is connected, there must be some edge $f$ with one end in $S$ and the other in $V \setminus S$.
- Since $c_f > c_e$, $T' = (T \setminus \{f\}) \cup \{e\}$ is a spanning tree of lower cost! **Error: $T'$ may not be a spanning tree!!**
Error in Proof: Example

Figure: Problematic example. \( S = \{1, 2, 7\} \), \( e = (7, 3) \), \( f = (1, 6) \). \( T - f + e \) is not a spanning tree.
Error in Proof: Example

Figure: Problematic example. $S = \{1, 2, 7\}$, $e = (7, 3)$, $f = (1, 6)$. $T - f + e$ is not a spanning tree.
Proof of Cut Property

Proof.

Suppose $e = (v, w)$ is not in MST $T$ and $e$ is min weight edge in cut $(S, V \setminus S)$. Wlog $v \in S$. 

![Graph Diagram]
Proof of Cut Property

Proof.

- Suppose \( e = (v, w) \) is not in MST \( T \) and \( e \) is min weight edge in cut \( (S, V \setminus S) \). Wlog \( v \in S \).

- \( T \) is spanning tree: there is a unique path \( P \) from \( v \) to \( w \) in \( T \).
Proof of Cut Property

Proof.

Suppose $e = (v, w)$ is not in MST $T$ and $e$ is min weight edge in cut $(S, V \setminus S)$. Wlog $v \in S$.

- $T$ is spanning tree: there is a unique path $P$ from $v$ to $w$ in $T$.

- Let $w'$ be the first vertex in $P$ belonging to $V \setminus S$; let $v'$ be the vertex just before it on $P$, and let $e' = (v', w')$.
Proof of Cut Property

Proof.

Suppose \( e = (v, w) \) is not in MST \( T \) and \( e \) is min weight edge in cut \((S, V \setminus S)\). Wlog \( v \in S \).

\( T \) is spanning tree: there is a unique path \( P \) from \( v \) to \( w \) in \( T \).

Let \( w' \) be the first vertex in \( P \) belonging to \( V \setminus S \); let \( v' \) be the vertex just before it on \( P \), and let \( e' = (v', w') \).

\( T' = (T \setminus \{e'\}) \cup \{e\} \) is spanning tree of lower cost. (Why?)
Proof of Cut Property (contd)

Observation

\[ T' = \left( T \setminus \{e'\} \right) \cup \{e\} \] is a spanning tree.

Proof.

\[ T' \] is connected.

\[ T' \] is a tree.
Proof of Cut Property (contd)

**Observation**

\[
T' = (T \setminus \{e'\}) \cup \{e\} \text{ is a spanning tree.}
\]

**Proof.**

\(T'\) is connected.

Removed \(e' = (v', w')\) from \(T\) but \(v'\) and \(w'\) are connected by the path \(P - f + e\) in \(T'\). Hence \(T'\) is connected if \(T\) is.

\(T'\) is a tree
**Proof of Cut Property (contd)**

**Observation**

\[ T' = (T \setminus \{e'\}) \cup \{e\} \] is a spanning tree.

**Proof.**

\( T' \) is connected.

Removed \( e' = (v', w') \) from \( T \) but \( v' \) and \( w' \) are connected by the path \( P - f + e \) in \( T' \). Hence \( T' \) is connected if \( T \) is.

\( T' \) is a tree

\( T' \) is connected and has \( n - 1 \) edges (since \( T \) had \( n - 1 \) edges) and hence \( T' \) is a tree.
 Lemma

Let $G$ be a connected graph with distinct edge costs, then the set of safe edges form a connected graph.

 Proof.

- Suppose not. Let $S$ be a connected component in the graph induced by the safe edges.
- Consider the edges crossing $S$, there must be a safe edge among them since edge costs are distinct and so we must have picked it.
Corollary

Let $G$ be a connected graph with distinct edge costs, then set of safe edges form the unique MST of $G$. 
Safe Edges form an MST

Corollary

Let $G$ be a connected graph with distinct edge costs, then set of safe edges form the unique MST of $G$.

Consequence: Every correct MST algorithm when $G$ has unique edge costs includes exactly the safe edges.
Lemma

*If e is an unsafe edge then no MST of G contains e.*

Proof.

Exercise. See textbook.

Note: Cut and Cycle properties hold even when edge costs are not distinct. Safe and unsafe definitions do not rely on distinct cost assumption.
Correctness of Prim’s Algorithm

**Prim’s Algorithm**

Pick edge with minimum attachment cost to current tree, and add to current tree.

**Proof of correctness.**

- If \( e \) is added to tree, then \( e \) is safe and belongs to every MST.

- Set of edges output is a spanning tree
Correctness of Prim’s Algorithm

### Prim’s Algorithm

Pick edge with minimum attachment cost to current tree, and add to current tree.

### Proof of correctness.

- If $e$ is added to tree, then $e$ is safe and belongs to every MST.
  - Let $S$ be the vertices connected by edges in $T$ when $e$ is added.

- Set of edges output is a spanning tree
Correctness of Prim’s Algorithm

Prim’s Algorithm
Pick edge with minimum attachment cost to current tree, and add to current tree.

Proof of correctness.

- If e is added to tree, then e is safe and belongs to every MST.
  - Let S be the vertices connected by edges in T when e is added.
  - e is edge of lowest cost with one end in S and the other in V \ S and hence e is safe.
- Set of edges output is a spanning tree
Correctness of Prim’s Algorithm

Prim’s Algorithm

Pick edge with minimum attachment cost to current tree, and add to current tree.

Proof of correctness.

- If $e$ is added to tree, then $e$ is safe and belongs to every MST.
  - Let $S$ be the vertices connected by edges in $T$ when $e$ is added.
  - $e$ is edge of lowest cost with one end in $S$ and the other in $V \setminus S$ and hence $e$ is safe.
- Set of edges output is a spanning tree
  - Set of edges output forms a connected graph: by induction, $S$ is connected in each iteration and eventually $S = V$. 
Correctness of Prim’s Algorithm

**Prim’s Algorithm**

Pick edge with minimum attachment cost to current tree, and add to current tree.

**Proof of correctness.**

- If $e$ is added to tree, then $e$ is safe and belongs to every MST.
  - Let $S$ be the vertices connected by edges in $T$ when $e$ is added.
  - $e$ is edge of lowest cost with one end in $S$ and the other in $V \setminus S$ and hence $e$ is safe.

- Set of edges output is a spanning tree
  - Set of edges output forms a connected graph: by induction, $S$ is connected in each iteration and eventually $S = V$.
  - Only safe edges added and they do not have a cycle.
Correctness of Kruskal’s Algorithm

Kruskal’s Algorithm

Pick edge of lowest cost and add if it does not form a cycle with existing edges.

Proof of correctness.

1. If $e = (u, v)$ is added to tree, then $e$ is safe

Set of edges output is a spanning tree: exercise
Correctness of Kruskal’s Algorithm

Kruskal’s Algorithm

Pick edge of lowest cost and add if it does not form a cycle with existing edges.

Proof of correctness.

- If \( e = (u, v) \) is added to tree, then \( e \) is safe
  - When algorithm adds \( e \) let \( S \) and \( S' \) be the connected components containing \( u \) and \( v \) respectively

Set of edges output is a spanning tree: exercise
Correctness of Kruskal’s Algorithm

Kruskal’s Algorithm

Pick edge of lowest cost and add if it does not form a cycle with existing edges.

Proof of correctness.

- If \( e = (u, v) \) is added to tree, then \( e \) is safe
  - When algorithm adds \( e \) let \( S \) and \( S' \) be the connected components containing \( u \) and \( v \) respectively
  - \( e \) is the lowest cost edge crossing \( S \) (and also \( S' \)).

- Set of edges output is a spanning tree: exercise
Correctness of Kruskal’s Algorithm

Kruskal’s Algorithm

Pick edge of lowest cost and add if it does not form a cycle with existing edges.

Proof of correctness.

- If \( e = (u, v) \) is added to tree, then \( e \) is safe
  - When algorithm adds \( e \) let \( S \) and \( S' \) be the connected components containing \( u \) and \( v \) respectively
  - \( e \) is the lowest cost edge crossing \( S \) (and also \( S' \)).
  - If there is an edge \( e' \) crossing \( S \) and has lower cost than \( e \), then \( e' \) would come before \( e \) in the sorted order and would be added by the algorithm to \( T \)
- Set of edges output is a spanning tree: exercise
Correctness of Reverse Delete Algorithm

**Reverse Delete Algorithm**
Consider edges in decreasing cost and remove an edge if it does not disconnect the graph.

**Proof of correctness.**
Argue that only unsafe edges are removed (see text book).
When edge costs are not distinct

**Heuristic argument:** Make edge costs distinct by adding a small tiny and different cost to each edge
When edge costs are not distinct

**Heuristic argument:** Make edge costs distinct by adding a small tiny and different cost to each edge

**Formal argument:** Order edges lexicographically to break ties

- $e_i \prec e_j$ if either $c(e_i) < c(e_j)$ or $(c(e_i) = c(e_j)$ and $i < j)$
When edge costs are not distinct

**Heuristic argument:** Make edge costs distinct by adding a small tiny and different cost to each edge

**Formal argument:** Order edges lexicographically to break ties

- \( e_i \prec e_j \) if either \( c(e_i) < c(e_j) \) or \( (c(e_i) = c(e_j) \) and \( i < j \))

- Lexicographic ordering extends to sets of edges. If \( A, B \subseteq E \), \( A \neq B \) then \( A \prec B \) if either \( c(A) < c(B) \) or \( (c(A) = c(B) \) and \( A \setminus B \) has a lower indexed edge than \( B \setminus A \))
When edge costs are not distinct

**Heuristic argument:** Make edge costs distinct by adding a small tiny and different cost to each edge

**Formal argument:** Order edges lexicographically to break ties

- $e_i \prec e_j$ if either $c(e_i) < c(e_j)$ or $c(e_i) = c(e_j)$ and $i < j$
- Lexicographic ordering extends to sets of edges. If $A, B \subseteq E$, $A \neq B$ then $A \prec B$ if either $c(A) < c(B)$ or $c(A) = c(B)$ and $A \setminus B$ has a lower indexed edge than $B \setminus A$
- Can order all spanning trees according to lexicographic order of their edge sets. Hence there is a unique MST.

Prim’s, Kruskal, and Reverse Delete Algorithms are optimal with respect to lexicographic ordering.
Edge Costs: Positive and Negative

- Algorithms and proofs don’t assume that edge costs are non-negative! MST algorithms work for arbitrary edge costs.
Edge Costs: Positive and Negative

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- Another way to see this: make edge costs non-negative by adding to each edge a large enough positive number. Why does this work for MSTs but not for shortest paths?
Edge Costs: Positive and Negative

- Algorithms and proofs don’t assume that edge costs are non-negative! MST algorithms work for arbitrary edge costs.
- Another way to see this: make edge costs non-negative by adding to each edge a large enough positive number. Why does this work for MSTs but not for shortest paths?
- Can compute *maximum* weight spanning tree by negating edge costs and then computing an MST.
Edge Costs: Positive and Negative

- Algorithms and proofs don’t assume that edge costs are non-negative! MST algorithms work for arbitrary edge costs.
- Another way to see this: make edge costs non-negative by adding to each edge a large enough positive number. Why does this work for MSTs but not for shortest paths?
- Can compute maximum weight spanning tree by negating edge costs and then computing an MST.
Part II

Data Structures for MST: Priority Queues and Union-Find
Implementing Prim’s Algorithm

- E is the set of all edges in G
  - S = \{1\}
  - T is empty (* T will store edges of a MST *)
  - while S \neq V
    - pick e = (v,w) in E such that
      - v \in S and w \in V - S
      - e has minimum cost
    - T = T \cup e
    - S = S \cup w
  - return the set T

Analysis
Implementing Prim’s Algorithm

E is the set of all edges in G
S = \{1\}
T is empty (* T will store edges of a MST *)
while S \neq V
    pick e = (v,w) in E such that
        v \in S and w \in V - S
        e has minimum cost
    T = T U e
    S = S U w
return the set T

Analysis

- Number of iterations \(= O(n)\), where \(n\) is number of vertices
Implementing Prim’s Algorithm

E is the set of all edges in G
S = {1}
T is empty (* T will store edges of a MST *)
while S =/= V
    pick e = (v,w) in E such that
    v ∈ S and w ∈ V - S
    e has minimum cost
    T = T U e
    S = S U w
return the set T

Analysis

- Number of iterations = O(n), where n is number of vertices
- Picking e is O(m) where m is the number of edges
Implementing Prim’s Algorithm

E is the set of all edges in G
S = \{1\}
T is empty (* T will store edges of a MST *)
while S \neq V
    pick e = (v,w) in E such that
    v \in S and w \in V - S
    e has minimum cost
    T = T \cup e
    S = S \cup w
return the set T

Analysis

- Number of iterations = \(O(n)\), where \(n\) is number of vertices
- Picking e is \(O(m)\) where \(m\) is the number of edges
- Total time \(O(nm)\)
More Efficient Implementation

E is the set of all edges in G
S = \{1\}
T is empty (* T will store edges of a MST *)
for v \not\in S, a(v) = \min_{w \in S} c(w,v)
for v \not\in S, e(v) = w such that w \in S and c(w,v) is minimum
while S =/= V
    pick v with minimum a(v)
    T = T U (e(v),v)
    S = S U v
    update arrays a and e
return the set T
More Efficient Implementation

E is the set of all edges in G
S = \{1\}
T is empty (* T will store edges of a MST *)
for v \notin S, a(v) = \min_{w \in S} c(w,v)
for v \notin S, e(v) = w such that w \in S and c(w,v) is minimum
while S =/= V
    pick v with minimum a(v)
    T = T U (e(v),v)
    S = S U v
    update arrays a and e
return the set T
More Efficient Implementation

E is the set of all edges in G
S = \{1\}
T is empty (* T will store edges of a MST *)
for v \notin S, a(v) = \min_{w \in S} c(w,v)
for v \notin S, e(v) = w \text{ such that } w \in S \text{ and } c(w,v) \text{ is minimum}
while S =/= V
    pick v with minimum a(v)
    T = T U (e(v),v)
    S = S U v
    update arrays a and e
return the set T

Maintain vertices in V \ S in a priority queue with key a(v)
Priority Queues

Data structure to store a set $S$ of $n$ elements where each element $v \in S$ has an associated real/integer key $k(v)$ such that the following operations

- **makeQ**: create an empty queue
- **findMin**: find the minimum key in $S$
- **extractMin**: Remove $v \in S$ with smallest key and return it
- **add($v$, $k(v)$)**: Add new element $v$ with key $k(v)$ to $S$
- **delete($v$)**: Remove element $v$ from $S$
- **decreaseKey($v$, $k'(v)$)**: decrease key of $v$ from $k(v)$ (current key) to $k'(v)$ (new key). Assumption: $k'(v) \leq k(v)$
- **meld**: merge two separate priority queues into one
Prim’s using priority queues

E is the set of all edges in G
S = {1}
T is empty (* T will store edges of a MST *)
for v \not\in S, a(v) = \min_{w \in S} c(w,v)
for v \not\in S, e(v) = w such that w \in S and c(w,v) is minimum
while S =/= V
    pick v with minimum a(v)
    T = T U (e(v),v)
    S = S U v
    update arrays a and e
return the set T

Maintain vertices in V \setminus S in a priority queue with key a(v)
Prim’s using priority queues

E is the set of all edges in G
S = \{1\}
T is empty (* T will store edges of a MST *)
for v \notin S, a(v) = \min_{w \in S} c(w,v)
for v \notin S, e(v) = w such that w \in S and c(w,v) is minimum
while S =/= V
    pick v with minimum a(v)
    T = T U (e(v),v)
    S = S U v
    update arrays a and e
return the set T

Maintain vertices in \( V \setminus S \) in a priority queue with key \( a(v) \)

- Requires \( O(n) \) extractMin operations
Prim’s using priority queues

E is the set of all edges in G
S = \{1\}
T is empty (* T will store edges of a MST *)
for v \notin S, a(v) = \min_{w \in S} c(w,v)
for v \notin S, e(v) = w such that w \in S and c(w,v) is minimum
while S \neq V
  pick v with minimum a(v)
  T = T U (e(v),v)
  S = S U v
  update arrays a and e
return the set T

Maintain vertices in V \setminus S in a priority queue with key a(v)
- Requires $O(n)$ extractMin operations
- Requires $O(m)$ decreaseKey operations
Running time of Prim’s Algorithm

\( O(n) \) extractMin operations and \( O(m) \) decreaseKey operations

- Using standard Heaps, extractMin and decreaseKey take \( O(\log n) \) time. Total: \( O((m + n)\log n) \)
- Using Fibonacci Heaps, \( O(\log n) \) for extractMin and \( O(1) \) (amortized) for decreaseKey. Total: \( O(n \log n + m) \).
Running time of Prim’s Algorithm

\( O(n) \) extractMin operations and \( O(m) \) decreaseKey operations

- Using standard Heaps, extractMin and decreaseKey take \( O(\log n) \) time. Total: \( O((m + n) \log n) \)
- Using Fibonacci Heaps, \( O(\log n) \) for extractMin and \( O(1) \) (amortized) for decreaseKey. Total: \( O(n \log n + m) \).

Prim’s algorithm and Dijkstra’s algorithms are similar. Where is the difference?
Kruskal’s Algorithm

Initially E is the set of all edges in G
T is empty (* T will store edges of a MST *)
while E is not empty
    choose e ∈ E of minimum cost
    if (T U {e} does not have cycles)
        add e to T
return the set T
Kruskal’s Algorithm

Initially E is the set of all edges in G
T is empty (* T will store edges of a MST *)
while E is not empty
    choose e ∈ E of minimum cost
    if (T ∪ {e} does not have cycles)
        add e to T
return the set T
Kruskal’s Algorithm

Initially E is the set of all edges in G
T is empty (* T will store edges of a MST *)
while E is not empty
    choose e ∈ E of minimum cost
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• Total time $O(m \log m) + O(mn) = O(mn)$
Implementing Kruskal’s Algorithm Efficiently

Sort edges in $E$ based on cost
$T$ is empty (* $T$ will store edges of a MST *)
each vertex $u$ is placed in a set by itself
while $E$ is not empty
  pick $e = (u,v) \in E$ of minimum cost
  if $u$ and $v$ belong to different sets
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    merge the sets containing $u$ and $v$
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Need a data structure to check if two elements belong to same set
and to merge two sets.
Union-Find Data Structure

Data Structure
Store disjoint sets of elements that supports the following operations

- `makeUnionFind(S)` returns a data structure where each element of `S` is in a separate set
Union-Find Data Structure

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- `makeUnionFind(S)` returns a data structure where each element of `S` is in a separate set
- `find(u)` returns the name of set containing element `u`. Thus, `u` and `v` belong to the same set iff `find(u) = find(v)`
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- `makeUnionFind(S)` returns a data structure where each element of `S` is in a separate set
- `find(u)` returns the name of set containing element `u`. Thus, `u` and `v` belong to the same set iff `find(u) = find(v)`
- `union(A, B)` merges two sets `A` and `B`. Typically: `union(find(u), find(v))`
Implementing Union-Find using Arrays and Lists

Using lists

- Each set stored as list with a name associated with the list.
- For each element \( u \in S \) a pointer to the its set. Array for pointers: \( \text{component}[u] \) is pointer for \( u \).
- \( \text{makeUnionFind}(S) \) takes \( O(n) \) time and space.
Example

A directed graph with vertices s, t, u, v, w, x, y, z, and edges connecting them. The edges are represented by arrows pointing from one vertex to another. The graph starts with vertex s and ends with vertex z.
Implementing Union-Find using Arrays and Lists

- \(\text{find}(u)\) reads the entry \(\text{component}[u]\): \(O(1)\) time
Implementing Union-Find using Arrays and Lists

- **find(u)** reads the entry component\[u\]: $O(1)$ time
- **union(A,B)**
Implementing Union-Find using Arrays and Lists

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find(u) reads the entry component[u]: O(1) time

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```

[Diagram showing the process of union-find operations]
**New Implementation**

As before use `component[u]` to store set of `u`.

Change to `union(A,B)`:

- with each set, keep track of its size
- assume `|A| ≤ |B|` for now
- Merge the list of `A` into that of `B`: `O(1)` time (linked lists)
- Update `component[u]` only for elements in the smaller set `A`
- Total `O(|A|)` time.
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find still takes \(O(1)\) time
Example

The smaller set (list) is appended to the largest set (list)
Improving the List Implementation for Union

**Question**

Is the improved implementation provably better or is it simply a nice heuristic?
Improving the List Implementation for Union

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Is the improved implementation provably better or is it simply a nice heuristic?

**Theorem**

*Any sequence of $k$ union operations, starting from makeUnionFind($S$) on set $S$ of size $n$, takes at most $O(k \log k)$.***
Improving the List Implementation for Union

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Is the improved implementation provably better or is it simply a nice heuristic?

**Theorem**

*Any sequence of $k$ union operations, starting from makeUnionFind($S$) on set $S$ of size $n$, takes at most $O(k \log k)$.*

**Corollary**

*Kruskal’s algorithm can be implemented in $O(m \log m)$ time.*

Sorting takes $O(m \log m)$ time, $O(m)$ finds take $O(m)$ time and $O(n)$ unions take $O(n \log n)$ time.
Amortized Analysis

Why does theorem work?

**Key Observation**

union(A, B) takes $O(|A|)$ time where $|A| \leq |B|$. Size of new set is $\geq 2|A|$. Cannot double too many times.
Proof of Theorem

Proof.

Any union operation involves at most 2 of the original one-element sets; thus at least $n - 2k$ elements have never been involved in a union. Also, the maximum size of any set (after $k$ unions) is $2^k$.

$\text{union}(A, B)$ takes $O(|A|)$ time where $|A| \leq |B|$.

Charge each element in $A$ a constant time to pay for $O(|A|)$ time.

How much does any element get charged?

If component $[v]$ is updated, the set containing $v$ doubles in size.

Component $[v]$ is updated at most $\log 2^k$ times.

Total number of updates is $2^k \log 2^k = O(k \log k)$. 

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- If \texttt{component}[v] is updated, set containing \( v \) \textit{doubles} in size.
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  - Total number of updates is \( 2k \log 2k = O(k \log k) \).
Better Data Structure

Maintain elements in a forest of in-trees; all elements in one tree belong to a set with root’s name.
Improving Worst Case Time

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Maintain elements in a forest of *in-trees*; all elements in one tree belong to a set with root’s name.

- \( \text{find}(u) \): Traverse from \( u \) to the root
Improving Worst Case Time

Better Data Structure

Maintain elements in a forest of *in-trees*; all elements in one tree belong to a set with root’s name.

- **find**(*u*): Traverse from *u* to the root
- **union**(*A, B*): Make root of *A* (smaller set) point to root of *B*. Takes $O(1)$ time.
Details of Implementation

Each element \( u \in S \) has a pointer \( \text{parent}(u) \) to its ancestor.

```python
makeUnionFind(S)
for each u in S
    parent(u) = u
find(u)
while (parent(u) ≠ u)
    u = parent(u)
return u
union(component(u), component(v)) (* parent(u) = u & parent(v) = v *)
if (|component(u)| ≤ |component(v)|)
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makeUnionFind(S)
    for each $u$ in $S$
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        $u = \text{parent}(u)$
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Theorem

The forest based implementation for a set of size $n$, has the following complexity for the various operations: makeUnionFind takes $O(n)$, union takes $O(1)$, and find takes $O(\log n)$. 

Proof. 

The height of a tree can increase by at most 1 only when the set containing a vertex $u$ changes its name. If the height of the tree containing $u$ increases, then the size of the set containing $u$ (at least) doubles. The maximum set size is $n$, so the height of any tree is at most $O(\log n)$. 

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Analysis

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- $\text{find}(u)$ depends on the height of tree containing $u$
Analysis

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The forest based implementation for a set of size $n$, has the following complexity for the various operations: `makeUnionFind` takes $O(n)$, `union` takes $O(1)$, and `find` takes $O(\log n)$.

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- `find(u)` depends on the height of tree containing $u$
- Height of $u$ increases by at most 1 only when the set containing $u$ changes its name
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- If height of $u$ increases then size of the set containing $u$ (at least) doubles.
- Maximum set size is $n$; so height of any tree is at most $O(\log n)$.
Further Improvements: Path Compression

Observation

Consecutive calls of $\text{find}(u)$ take $O(\log n)$ time each, but they traverse the same sequence of pointers.
Further Improvements: Path Compression

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Consecutive calls of $\text{find}(u)$ take $O(\log n)$ time each, but they traverse the same sequence of pointers.

Idea: Path Compression

Make all nodes encountered in the $\text{find}(u)$ point to root.
Path Compression: Example

Before find(u):

After find(u):

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Path Compression

```python
find(u):
    if (parent(u) ≠ u)
        parent(u) = find(parent(u))
    return parent(u)
```
Path Compression

find(u):
    if (parent(u) \neq u)
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Question

Does Path Compression help?

Theorem

With Path Compression, k operations (find and/or union) take \(O(k \alpha(k, \min\{k, n\}))\) time where \(\alpha\) is the inverse Ackermann function.
Path Compression

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Ackerman and Inverse Ackerman Functions

Ackerman function $A(m, n)$ defined for $m, n \geq 0$ recursively

$$A(m, n) = \begin{cases} 
  n + 1 & \text{if } m = 0 \\
  A(m - 1, 1) & \text{if } m > 0 \text{ and } n = 0 \\
  A(m - 1, A(m, n - 1)) & \text{if } m > 0 \text{ and } n > 0 
\end{cases}$$
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$A(3, n) = 2^{n+3} - 3$

$A(4, 3) = 2^{65536} - 3$

$\alpha(m, n)$ is inverse Ackerman function defined as

$$\alpha(m, n) = \min\{ i \mid A(i, \lfloor m/n \rfloor) \geq \log_2 n \}$$
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For all practical purposes $\alpha(m, n) \leq 5$
Amazing result:

**Theorem (Tarjan)**

*For UnionFind, any data structure in the pointer model requires $O(m\alpha(m, n))$ time for $m$ operations.*
Running time of Kruskal’s Algorithm

Using Union-Find data structure:

- $O(m)$ find operations (two for each edge)
- $O(n)$ union operations (one for each edge added to $T$)
- Total time: $O(m \log m)$ for sorting plus $O(m \alpha(n))$ for union-find operations. Thus $O(m \log m)$ time despite the improved Union-Find data structure.
Best Known Asymptotic Running Times for MST

Prim’s algorithm using Fibonacci heaps: $O(n \log n + m)$. If $m$ is $O(n)$ then running time is $\Omega(n \log n)$. 
Best Known Asymptotic Running Times for MST

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Question

Is there a linear time ($O(m + n)$ time) algorithm for MST?
Best Known Asymptotic Running Times for MST

Prim’s algorithm using Fibonacci heaps: \( O(n \log n + m) \).
If \( m \) is \( O(n) \) then running time is \( \Omega(n \log n) \).

Question

Is there a linear time (\( O(m + n) \) time) algorithm for MST?

- \( O(m \log^* m) \) time [Fredman and Tarjan '1986]
- \( O(m + n) \) time using bit operations in RAM model [Fredman and Willard 1993]
- \( O(m + n) \) expected time (randomized algorithm) [Karger, Klein and Tarjan '1985]
- \( O((n + m)\alpha(m, n)) \) time [Chazelle '97]
- Still open: is there an \( O(n + m) \) time deterministic algorithm in the comparison model?