

Greedy Algorithms

Greedy Technique

- What is it?
 - Quick and dirty approach to solving optimization problems
 - Not necessarily optimal
- Problems explored
 - Coin changing problem
 - Minimum spanning tree algorithms
 - Dijkstra's algorithm for single source shortest paths
 - Knapsack problem

Optimization problems

- An **optimization** problem:
 - For a problem to solve, there are an **objective function** and a set of **constraints**
 - Find a **feasible** solution for the given instance for which the objective function has an optimal value (either maximum or minimum depending on the problem being solved)
 - A **feasible** solution satisfies the problem's constraints
 - The **constraints** specify the limitations on the required solutions
- **An example in the next slide**

Coin changing problem

- Problem: Return correct change using a minimum number of US coins.
- Greedy choice: Pick the coin with the highest value
- A greedy solution: next slide
- The amount owed = 37 cents.
 - The change is: 1 quarter, 1 dime, 2 cents.
- Solution is optimal when US coins are used. Why is it optimal?

A greedy solution:

Input: Set of coins, *amount-owed*

change = {}

while (more coin-sizes && *valueof(change)* < *amount-owed*)
{

// Selection

Choose the largest remaining coin

// feasibility check

if (adding the coin makes the *valueof(change)* exceed the *amount-owed*)

then reject the coin

else add coin to *change*

// check if solved

if (*valueof(change)* == *amount-owed*)

then return *change*

}

return “failed to compute change”

Elements of the Greedy Strategy

- Cast problem as one in which you make a greedy choice and are left with one sub-problem to solve.
- Cost-benefit analysis for a greedy choice, e.g., the number of the coins used vs. the remaining amount of the change you owe

A greedy solution is not always optimal!

- Reconsider the Coin Changing problem
 - Suppose you live in Alice's Wonderland where you have 12 cent coins in addition to US coins
 - Suppose you owe 16 cents
 - The greedy solution chooses a 12 cent coin and four 1 cent coins → 5 coins
 - An optimal solution is one dime, one nickel, and one cent → 3 coins

- Some greedy algorithms provides optimal solutions
 - A **proof** is needed
 - A **counter example** shows that a greedy algorithm does not provide an optimal solution

Greedy vs. Dynamic Programming

- Greedy algorithms make **good local choices** in the hope that they result in an optimal solution
 - In each step, just make a choice that seems best at the moment
 - Solve the remaining sub-problem in the next step by making another greedy choice
- ➔ Produces a feasible solution but does not necessarily end up with an optimal solution

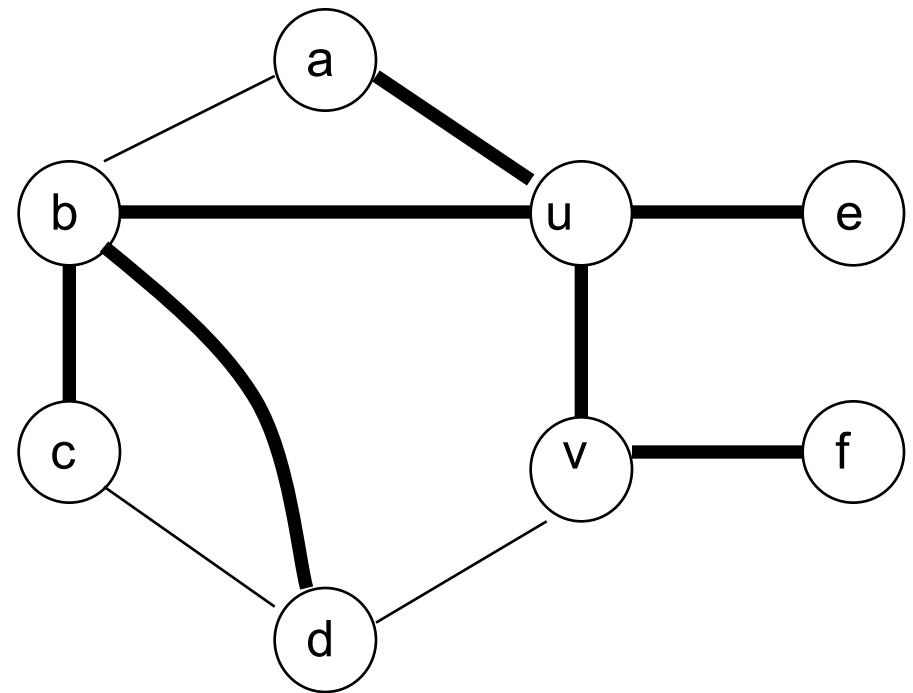
- A greedy algorithm never reconsiders its choices
 - Dynamic programming is exhaustive, and makes decisions based on all the previous decisions, potentially reconsidering previous choices (look up previous solutions)
- In an earlier lecture on dynamic programming, we saw both greedy and dynamic programming approaches for finding an Optimal BST (Binary Search Tree)
 - A greedy approach locating the highest probability node at the root or trying to minimize the tree depth does not necessarily gives you an optimal solution

Greedy Minimum Spanning Tree Algorithms

- Prim's Algorithm
- Kruskal's Algorithm

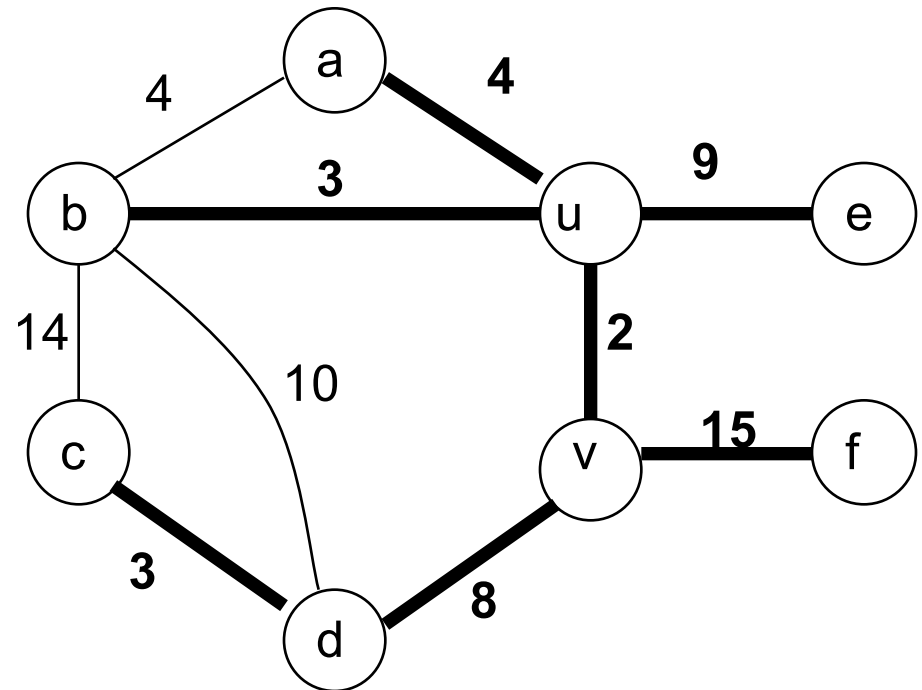
What is A Spanning Tree?

- A *spanning* tree for an undirected graph $G=(V,E)$ is a **subgraph** of G that is a **tree** and **contains all the vertices** of G
- Can a graph have more than one spanning tree?
- Can a disconnected graph have a spanning tree?



Minimum Spanning Tree

- The *weight* of a subgraph is the sum of the weights of its edges.
- A *minimum spanning tree* for a weighted graph is a spanning tree with the minimum weight
- Can a graph have more than one minimum spanning tree?



MST T : $w(T) = \sum_{(u,v) \in T} w(u,v)$ is minimized

Example of a Problem that translates into a MST

The Problem

- Several pins of an electronic circuit must be connected using the least amount of wire.

Modeling the Problem

- The graph is a complete, undirected graph $G = (V, E, W)$, where V is the set of pins, E is the set of all possible interconnections between the pairs of pins and $w(e)$ is the length of the wire needed to connect the pair of vertices.
- Find a minimum spanning tree.

Greedy Choice

We will show two ways to build a minimum spanning tree.

- *Prim's algorithm*
 - *A MST can be grown from the current spanning tree by adding the nearest vertex and the edge connecting the nearest vertex to the MST*
- *Kruskal's algorithm*
 - *A MST can be grown from a forest of spanning trees by adding the smallest edge connecting two spanning trees*

Notation

- Tree-vertices: in the tree constructed so far
- Non-tree vertices: rest of vertices

Prim's Selection rule

- Select the minimum weight edge between a tree-node and a non-tree node and add it to the tree

Key idea of Prim's algorithm

Select a vertex to be a tree-node

while (there are non-tree vertices)

{

if (there is no edge connecting a tree node with a non-tree node)

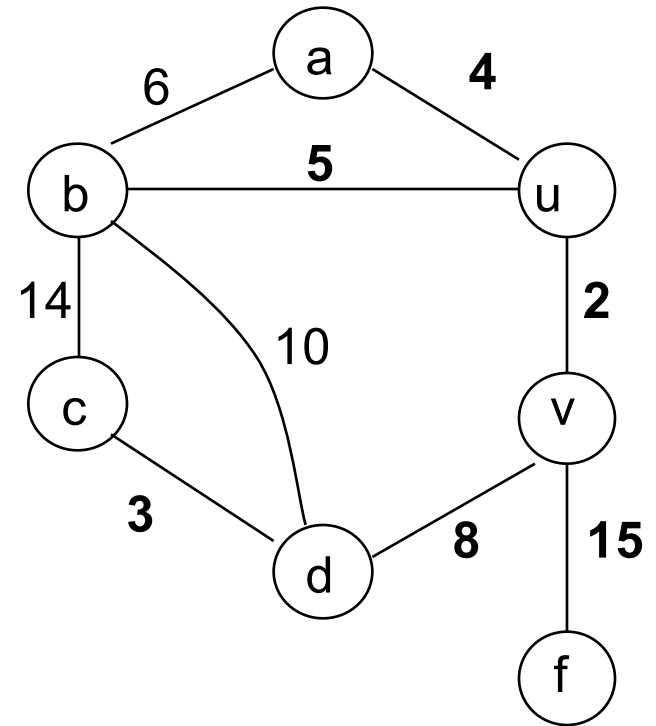
return “no spanning tree”

 select an edge of minimum weight between a tree node and a non-tree node

 add the selected edge and its new vertex to the tree

}

return tree



Prim's algorithm

source: **Algorithms** by [Sanjoy Dasgupta](#), [Christos Papadimitriou](#), [Umesh Vazirani](#), McGraw Hill, 2006

procedure prim(G, w)

Input: A connected undirected graph $G = (V, E)$ with edge weights w_e

Output: A minimum spanning tree defined by the array `prev`

for all $u \in V$:

$\text{cost}(u) = \infty$

$\text{prev}(u) = \text{nil}$

Pick any initial node u_0

$\text{cost}(u_0) = 0$

$w[i][j] = 0$ if $i=j$;

edge weight if there is an edge (i,j) ; or
infinity if no edge (i, j) exists

$H = \text{makequeue}(V)$ (priority queue, using cost-values as keys)

while H is not empty:

$v = \text{deletemin}(H)$

 for each $\{v, z\} \in E$:

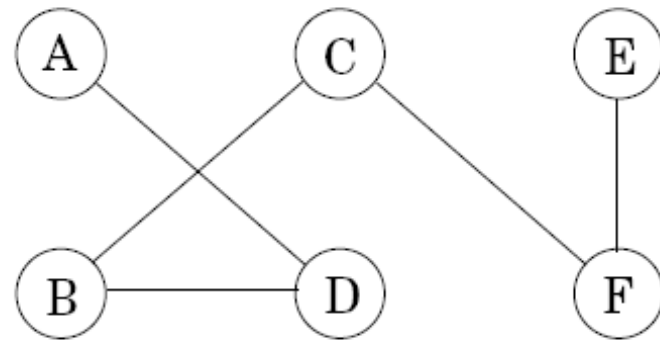
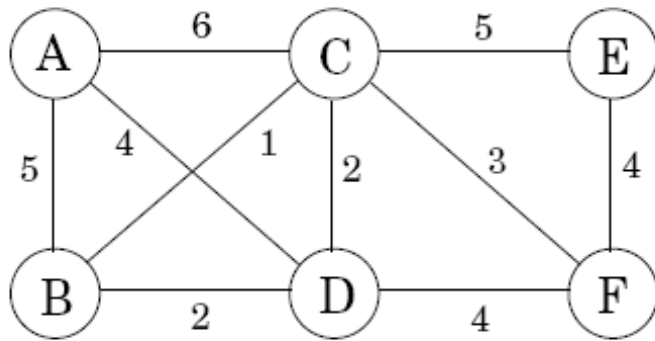
 if $\text{cost}(z) > w(v, z)$:

$\text{cost}(z) = w(v, z)$

$\text{prev}(z) = v$

$\text{decreasekey}(H, z)$

Example



S : set of
tree
vertices

Set S	A	B	C	D	E	F
$\{\}$	0/nil	∞ /nil	∞ /nil	∞ /nil	∞ /nil	∞ /nil
A		5/ A	6/ A	4/ A	∞ /nil	∞ /nil
A, D		2/ D	2/ D		∞ /nil	4/ D
A, D, B			1/ B		∞ /nil	4/ D
A, D, B, C					5/ C	3/ C
A, D, B, C, F					4/ F	

cost/prev

Implementation

- Queue can be implemented as an array or heap
- Time complexity changes based on the implementation of the queue
 - More details next

Prim's algorithm

Source: A free online algorithms book available at
<http://www.cs.berkeley.edu/~vazirani/algorithms.html>

procedure prim(G, w)

Input: A connected undirected graph $G = (V, E)$ with edge weights w_e

Output: A minimum spanning tree defined by the array prev

for all $u \in V$:
 $\text{cost}(u) = \infty$
 $\text{prev}(u) = \text{nil}$
Pick any initial node u_0
 $\text{cost}(u_0) = 0$

$\Theta(V)$

$\Theta(1)$

$H = \text{makequeue}(V)$ (priority queue, using cost-values as keys)

while H is not empty: $\leftarrow \Theta(V)$

$v = \text{deletemin}(H)$

for each $\{v, z\} \in E$:

 if $\text{cost}(z) > w(v, z)$:

$\text{cost}(z) = w(v, z)$

$\text{prev}(z) = v$

$\text{decreasekey}(H, z)$

So, the total time complexity is
 $O(V * \text{deletemin}) + O(E * \text{decreasekey})$

Note that decreasekey is executed
maximum E times to find an MST

Prim's algorithm

- Time complexity
 - $O(V * \text{deletemin}) + O(E * \text{decreasekey})$
 - Array: deletemin is $O(V)$ and decreasekey is $O(1) \rightarrow O(V^2)$
 - Heap: deletemin is $O(\lg V)$ and decrease key is $O(\lg V) \rightarrow O(E \lg V)$
 - Which is better?

Lemma 1

- Let $G = (V, E)$ be a connected, weighted undirected graph. Let T be a promising subset of E . Let Y be the set of vertices connected by the edges in T .
- **If e is a minimum weight edge that connects a vertex in Y to a vertex in $V - Y$, then $T \cup \{e\}$ is promising.**

Note: A feasible set is *promising* if it can be extended to produce not only a solution but an optimal solution.

In this algorithm, a feasible set of edges is *promising* if it is a subset of a MST for the connected graph G .

Outline of Proof of Correctness of Lemma 1

- T is the promising subset and e is the minimum cost edge of Lemma 1
- Let T' be the MST such that $T \subset T'$
- We will show that if $e \notin T'$ then there must be another MST T'' such that $T \cup \{e\} \subseteq T''$.

Proof has 4 stages (shown in the following slides):

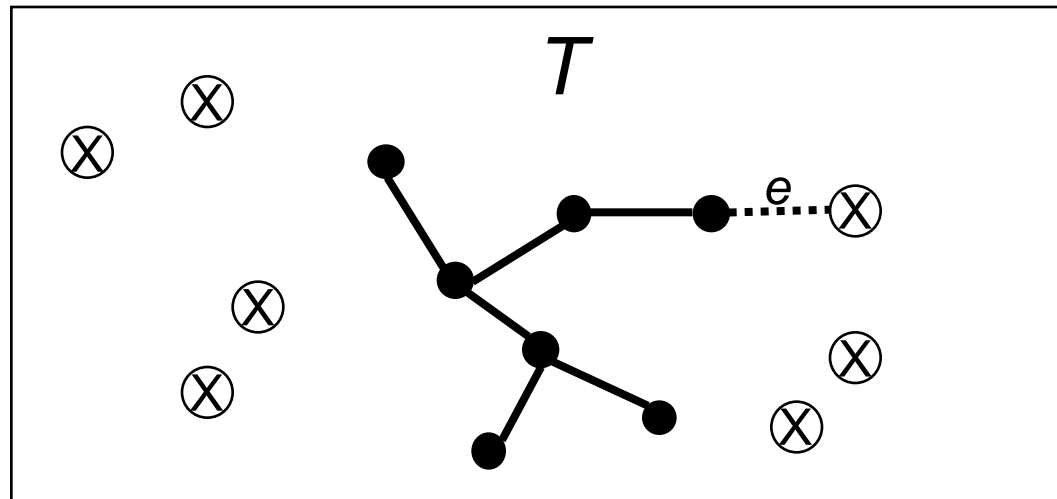
1. Adding e to T' , creates a cycle in $T' \cup \{e\}$.
2. Cycle contains another edge $e' \in T'$ but $e' \notin T$
3. $T'' = T' \cup \{e\} - \{e'\}$ is a spanning tree
4. T'' is a MST

Lemma 1

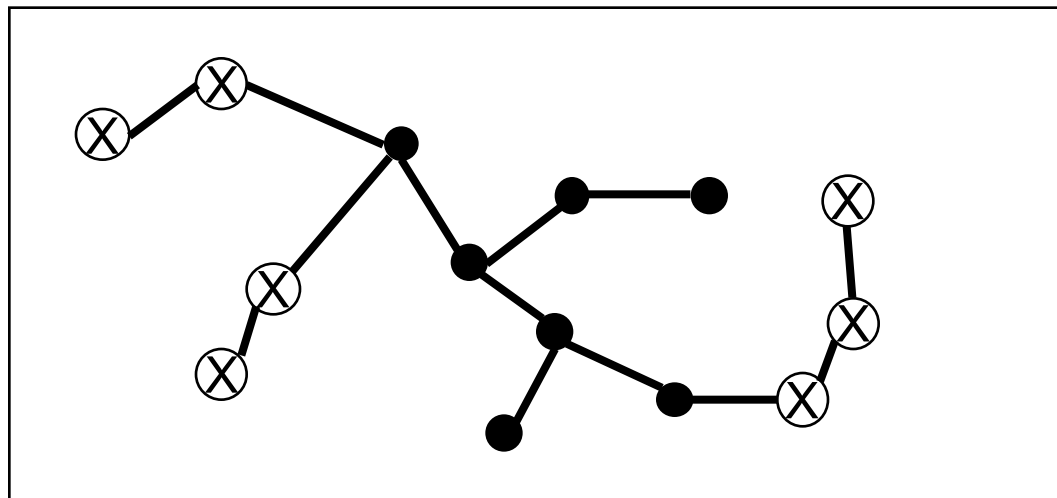
The Promising Set of Edges Selected by Prim

● $\in Y$

⊗ $\in V - Y$



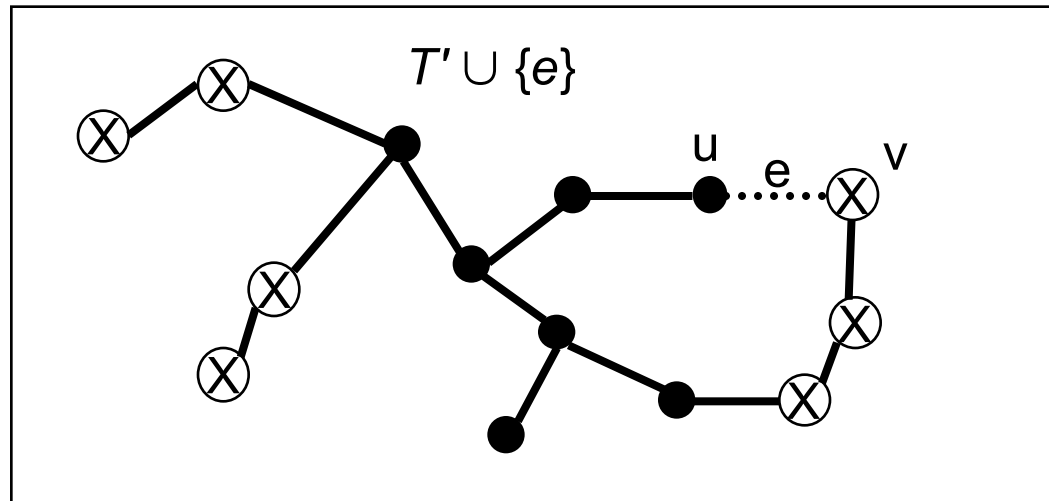
MST T' but $e \notin T'$



Lemma 1

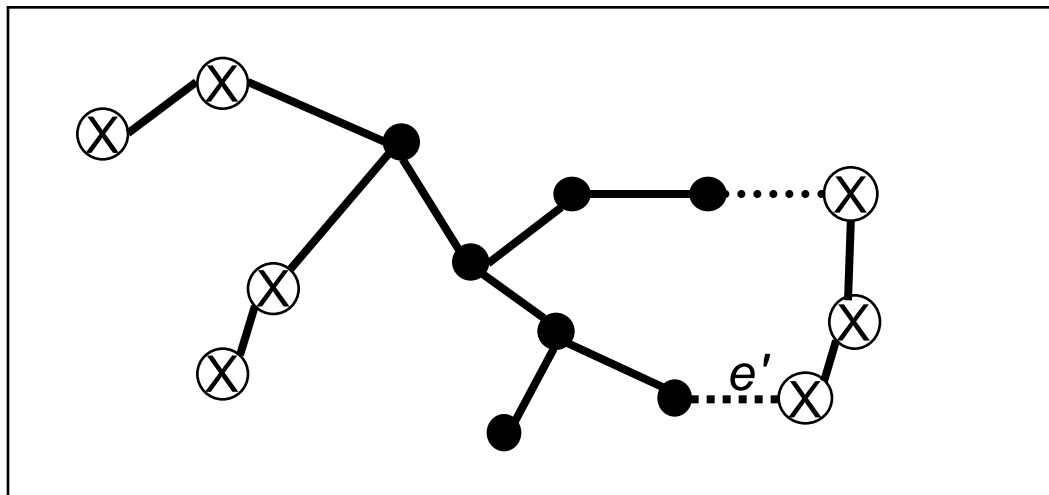
Since T' is a spanning tree, adding e creates a cycle.

● $\in Y$
 ⊗ $\in V - Y$



Stage 1

In T' there is a path from $u \in Y$ to $v \in V - Y$. Therefore the path must include another edge e' with one vertex in Y and the other in $V - Y$.

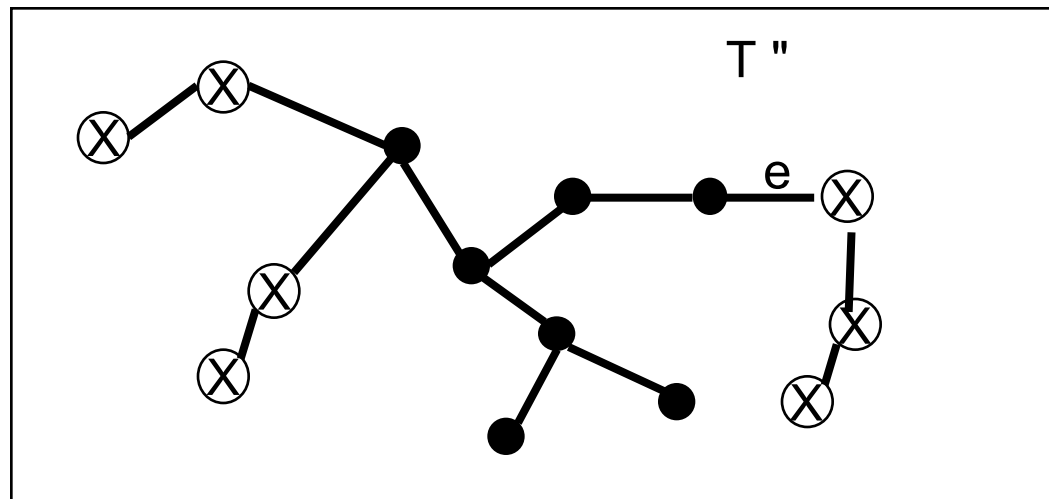


Stage 2

Lemma 1

- If we remove e' from $T' \cup \{e\}$ the cycle disappears.
- $T'' = T' \cup \{e\} - \{e'\}$ is connected.

$\bullet \in Y$
 $\otimes \in V - Y$



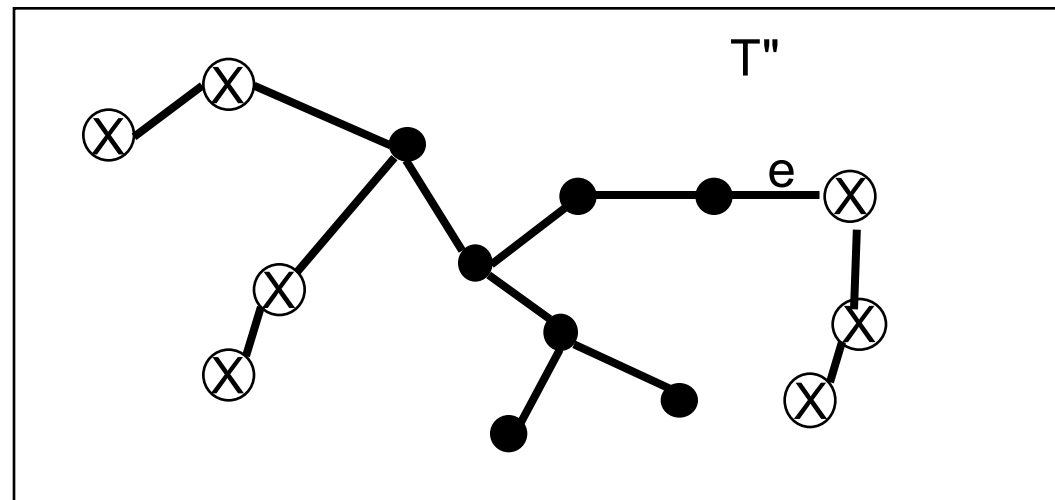
Stage 3

$w(e) \leq w(e')$ due to the way *Prim* picks the next edge

Lemma 1

- $w(e) \leq w(e')$ because of the way *Prim* picks the next edge
- The weight of T'' , $w(T'') = w(T') + w(e) - w(e') \leq w(T')$.
- But $w(T') \leq w(T'')$ because T' is a MST.
- So $w(T') = w(T'')$ and T'' is a MST

● $\in Y$
 ⊗ $\in V - Y$



Stage 4

Conclusion $T \cup \{e\}$ is promising

Theorem: Prim's Algorithm always produces a minimum spanning tree.

Proof by induction on the set T of promising edges.

1. Base case: Initially, $T = \emptyset$ is promising.
2. Induction hypothesis: The current set of edges T selected by Prim is promising.
3. Induction step: After Prim adds the edge e , $T \cup \{e\}$ is promising.

Proof: $T \cup \{e\}$ is promising by Lemma 1.

Conclusion: When G is connected, T produced by Prim is a MST.