

Data Structures and Algorithms

UBCO Master of Data Science – DATA 532



Recap

We looked various applications for searching in Graphs

We specifically looked at two algorithms

- Breadth First Search
- Depth First Search

Very briefly talked about other algorithms that are of interest in Graph theory

Today...

Dynamic Programming

- Forward Approach
- Backward Approach

Example of Dynamic Programming (Hands on)

Fibonacci sequence

Fibonacci sequence: 0 , 1 , 1 , 2 , 3 , 5 , 8 , 13 , 21 , ...

$$F_i = i \quad \text{if } i \leq 1$$

$$F_i = F_{i-1} + F_{i-2} \quad \text{if } i \geq 2$$

Solved by a recursive program: $O(N)$

Much replicated computation is done.

It should be solved by a simple loop.

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Dynamic Programming

Dynamic Programming is an algorithm design method that can be used when the solution to a problem may be viewed as the result of a sequence of decisions

Comparison with divide-and-conquer

Divide-and-conquer algorithms split a problem into separate sub problems, solve the sub problems, and combine the results for a solution to the original problem

- Example: Quicksort
- Example: Mergesort
- Example: Binary search

Divide-and-conquer algorithms can be thought of as **top-down** algorithms

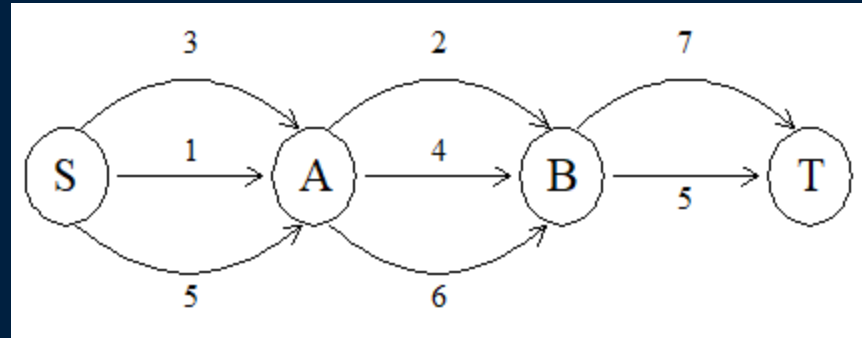
Comparison with divide-and-conquer

In contrast, a **dynamic programming algorithm** proceeds by solving small problems, remembering the results, then combining them to find the solution to larger problems

Dynamic programming can be thought of as **bottom-up**

The shortest path

To find a shortest path in a multi-stage graph



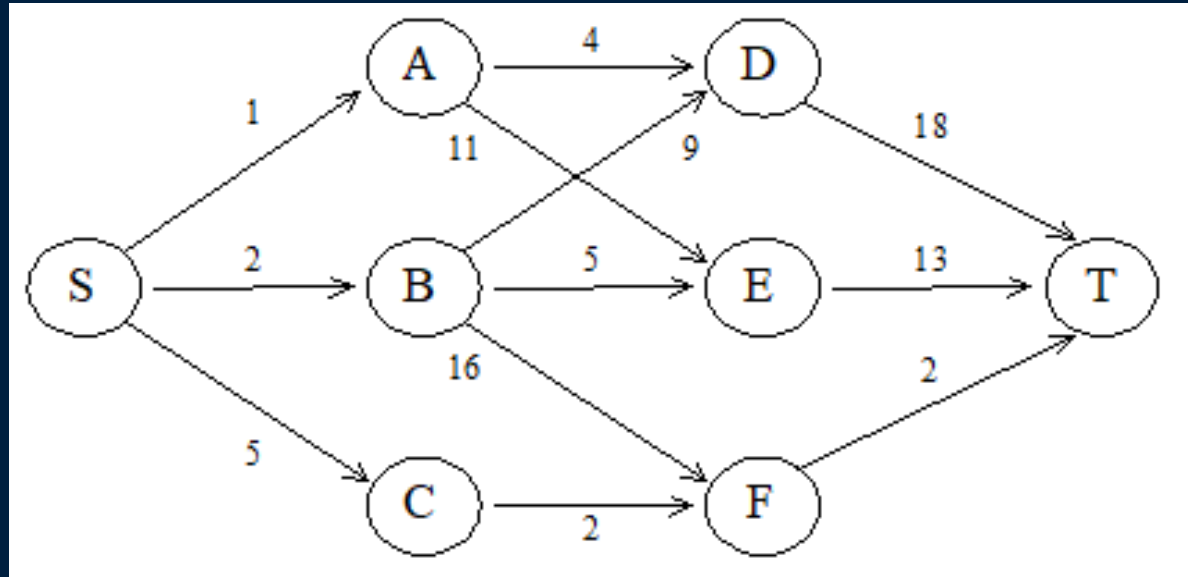
Apply the greedy method :

the shortest path from S to T :

$$1 + 2 + 5 = 8$$

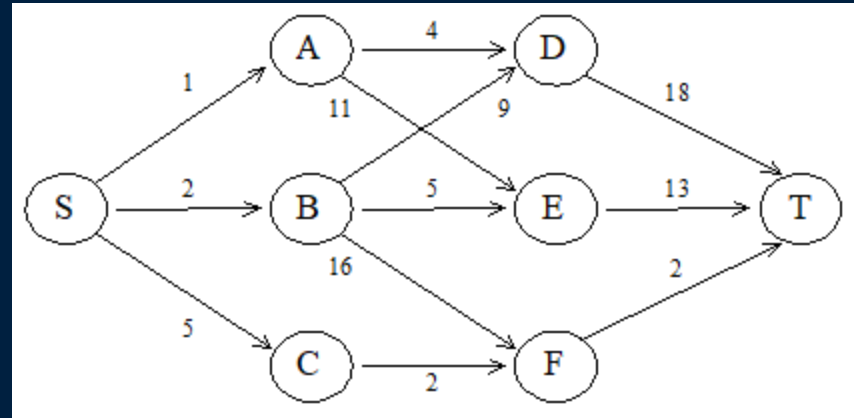
The shortest path in multistage graphs

e.g.



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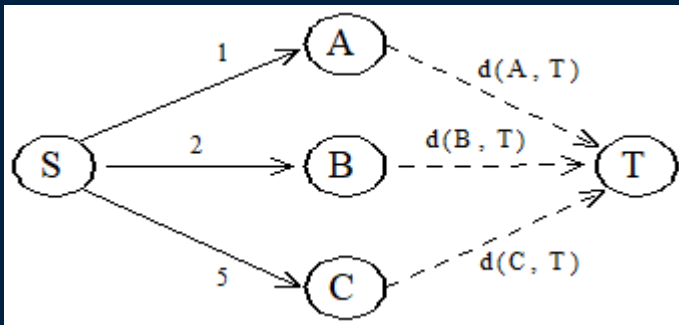
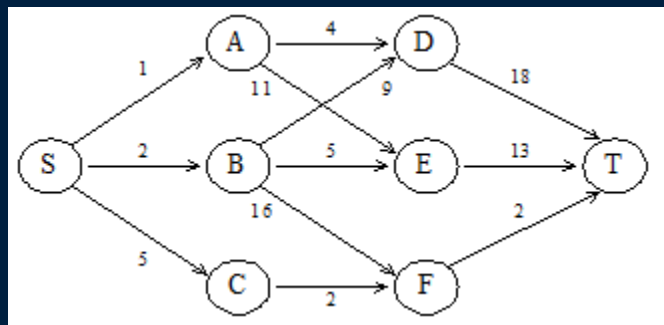
The greedy method can not be applied to this case: (S, A, D, T) $1+4+18 = 23$.

The real shortest path is:

(S, C, F, T) $5+2+2 = 9$.

Dynamic programming approach

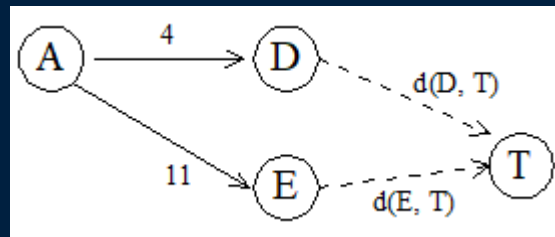
Dynamic programming approach (forward approach):



$$d(S, T) = \min\{1+d(A, T), 2+d(B, T), 5+d(C, T)\}$$

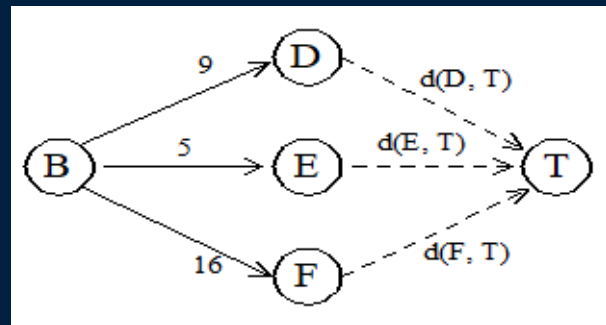
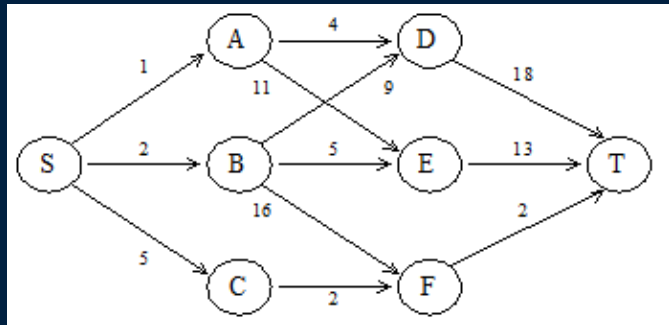
- $$d(A, T) = \min\{4+d(D, T), 11+d(E, T)\}$$

$$= \min\{4+18, 11+13\} = 22.$$



$$d(B, T) = \min\{9+d(D, T), 5+d(E, T), 16+d(F, T)\}$$

$$= \min\{9+18, 5+13, 16+2\} = 18.$$



$$d(C, T) = \min\{2+d(F, T)\} = 2+2 = 4$$

$$d(S, T) = \min\{1+d(A, T), 2+d(B, T), 5+d(C, T)\}$$

$$= \min\{1+22, 2+18, 5+4\} = 9.$$

The above way of reasoning is called backward reasoning.

Backward approach (forward reasoning)

$$d(S, A) = 1$$

$$d(S, B) = 2$$

$$d(S, C) = 5$$

$$d(S, D) = \min\{d(S, A) + d(A, D), d(S, B) + d(B, D)\}$$

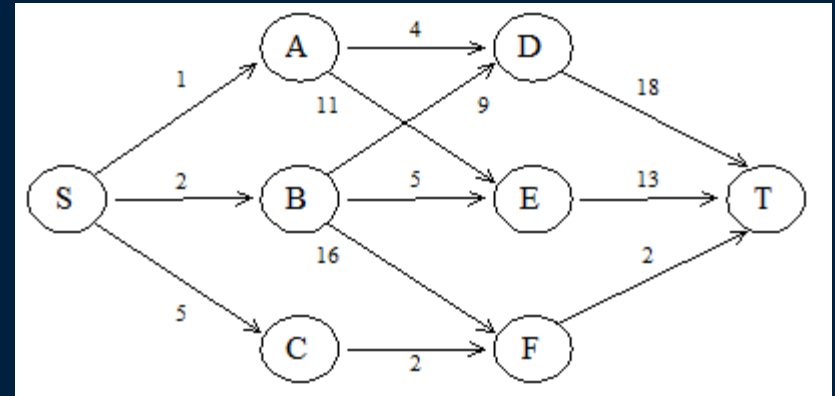
$$= \min\{1 + 4, 2 + 9\} = 5$$

$$d(S, E) = \min\{d(S, A) + d(A, E), d(S, B) + d(B, E)\}$$

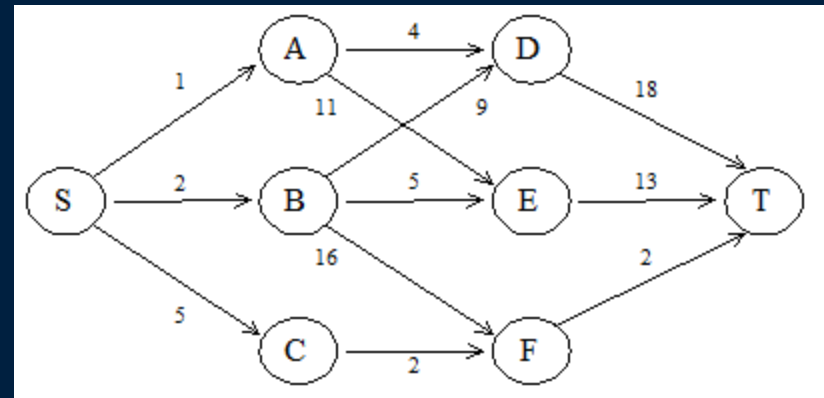
$$= \min\{1 + 11, 2 + 5\} = 7$$

$$d(S, F) = \min\{d(S, B) + d(B, F), d(S, C) + d(C, F)\}$$

$$= \min\{2 + 16, 5 + 2\} = 7$$



$$\begin{aligned}
 d(S,T) &= \min\{d(S, D)+d(D, T), d(S,E)+ \\
 &\quad d(E,T), d(S, F)+d(F, T)\} \\
 &= \min\{ 5+18, 7+13, 7+2 \} \\
 &= 9
 \end{aligned}$$



The principle of optimality, I

Dynamic programming is a technique for finding an *optimal* solution

The **principle of optimality** applies if the optimal solution to a problem can be obtained by combining the optimal solutions to all subproblems.

The principle of optimality, I

Example: Consider the problem of making $N\text{¢}$ with the fewest number of coins

- Either there is an $N\text{¢}$ coin, or
- The set of coins making up an optimal solution for $N\text{¢}$ can be divided into two nonempty subsets, $n_1\text{¢}$ and $n_2\text{¢}$
 - If either subset, $n_1\text{¢}$ or $n_2\text{¢}$, can be made with fewer coins, then clearly $N\text{¢}$ can be made with fewer coins, hence solution was *not* optimal

The principle of optimality, II

The principle of optimality holds if

- Every optimal solution to a problem contains...
- ...optimal solutions to all subproblems

The principle of optimality does *not* say

- If you have optimal solutions to all subproblems...
- ...then you can combine them to get an optimal solution

The principle of optimality, II

Example: In coin problem,

- The optimal solution to $7¢$ is $5¢ + 1¢ + 1¢$, *and*
- The optimal solution to $6¢$ is $5¢ + 1¢$, *but*
- The optimal solution to $13¢$ is *not* $5¢ + 1¢ + 1¢ + 5¢ + 1¢$

But there is *some* way of dividing up $13¢$ into subsets with optimal solutions that will give an optimal solution for $13¢$

- Hence, the principle of optimality holds for this problem

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Principle of optimality

Principle of optimality: Suppose that in solving a problem, we have to make a sequence of decisions D_1, D_2, \dots, D_n . If this sequence is optimal, then the last k decisions, $1 < k < n$ must be optimal.

e.g. the shortest path problem

If i, i_1, i_2, \dots, j is a shortest path from i to j , then i_1, i_2, \dots, j must be a shortest path from i_1 to j

In summary, if a problem can be described by a multistage graph, then it can be solved by dynamic programming.

Dynamic programming

Forward approach and backward approach:

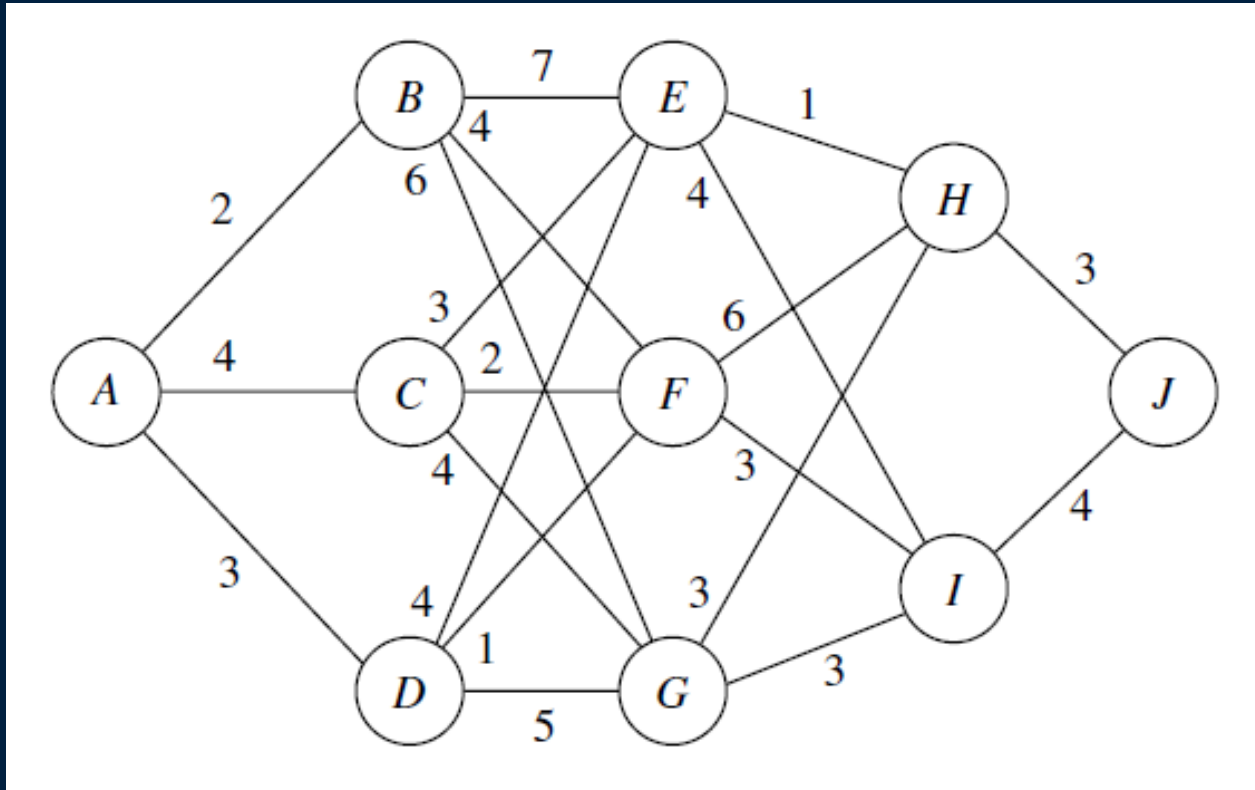
- Note that if the recurrence relations are formulated using the forward approach then the relations are solved backwards . i.e., beginning with the last decision
- On the other hand if the relations are formulated using the backward approach, they are solved forwards.

To solve a problem by using dynamic programming:

- Find out the recurrence relations.
- Represent the problem by a multistage graph.

Hands on Example

Stage Coach Problem – Hands on Example



Recap

We looked introduction to Dynamic Programming

Notion of Forward Approach (Backward Reasoning) and vice-versa

Principle of Optimality in Dynamic Programming

Hands on Example



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