

## Algolab 2016 – STL Week 2

28th September 2016

## Problem: Barber shop

A barber takes  $L$  minutes to cut a customer's hair.

- ▶  $n$  customers arrive at times  $t_0, \dots, t_{n-1}$ .
- ▶ The last customer leaves at time  $T$ .
- ▶ What is  $L$ ?

## Problem: Barber shop

A barber takes  $L$  minutes to cut a customer's hair.

- ▶  $n$  customers arrive at times  $t_0, \dots, t_{n-1}$ .
- ▶ The last customer leaves at time  $T$ .
- ▶ What is  $L$ ?
- ▶ The barber starts cutting the next customer's hair as soon as he is finished with his current customer.
- ▶ But maybe he has to wait for the next customer to arrive.

# Reformulation

Let us say that  $L$  is **too small** if the last customer will leave **before time  $T$** , assuming the barber needs  $L$  minutes for a haircut.

We need to find the smallest  $L$  that is not too small.

# Reformulation

Let us say that  $L$  is **too small** if the last customer will leave **before time  $T$** , assuming the barber needs  $L$  minutes for a haircut.

We need to find the smallest  $L$  that is not too small.

**Simpler problem:** check whether a **fixed  $L$**  is too small.

To check if a fixed  $L$  is too small:

To check if a fixed  $L$  is too small:

- ▶ Precomputation: sort the arrival times in increasing order.

```
1  sort(t.begin(), t.end());
```

To check if a fixed  $L$  is too small:

- ▶ Precomputation: sort the arrival times in increasing order.

```
1  sort(t.begin(), t.end());
```

- ▶ Check if  $L$  is too small:

```
1  bool too_small(int L) {  
2      int time = 0;  
3      for (int i = 0; i < n; i++) {  
4          if (t[i] <= time)  
5              time += L;  
6          else  
7              time = t[i] + L;  
8      }  
9      return (time < T);  
10 }
```



## Trick/technique (Sorting)

Sorting can be a powerful pre-computation step.

To sort a vector, always use the `std::sort` function from the `algorithm` header.

- ▶  $O(n \log n)$  time for the pre-computation
- ▶  $O(n)$  time per call of `too_small`

- ▶  $O(n \log n)$  time for the pre-computation
- ▶  $O(n)$  time per call of `too_small`

How can we find the smallest  $L$  that is not too small?

# Binary search

- ▶ The property of **not being too small** is **monotone**.

# Binary search

- ▶ The property of **not being too small** is **monotone**.
- ▶ So we can use **binary search** to efficiently find the smallest  $L$  with this property.

# Binary search

- ▶ The property of **not being too small** is **monotone**.
- ▶ So we can use **binary search** to efficiently find the smallest  $L$  with this property.
- ▶ First, we find an upper bound on the smallest  $L$ :

```
1 int lmin = 0, lmax = 1;  
2  
3 while (too_small(lmax)) lmax *= 2;
```

# Binary search

- ▶ The property of **not being too small** is **monotone**.
- ▶ So we can use **binary search** to efficiently find the smallest  $L$  with this property.
- ▶ First, we find an upper bound on the smallest  $L$ :

```
1  int lmin = 0, lmax = 1;
2
3  while (too_small(lmax)) lmax *= 2;
```

- ▶ Now we do the binary search:

```
1  while (lmin != lmax) {
2      int p = (lmin+lmax)/2;
3      if (too_small(p))
4          lmin = p+1;
5      else
6          lmax = p;
7  }
8  L = lmin;
```

## In general

The **problem**: find the smallest  $k$  that is 'large enough'.

For a **fixed**  $k$ , you can check efficiently if it is 'large enough'.

How to find the smallest  $k$  efficiently?



## In general

The **problem**: find the smallest  $k$  that is 'large enough'.

For a **fixed**  $k$ , you can check efficiently if it is 'large enough'.

How to find the smallest  $k$  efficiently?

### Trick/technique (Binary search)

In such situations, we can use **binary search** to find the optimal  $k$ .

The running time is multiplied only with a factor of  $O(\log K)$ , where  $K$  is the smallest  $k$  that is large enough.

## Problem: Deck of cards

Given numbers  $v_0, \dots, v_{n-1}$ , minimize

$$\left| k - \sum_{i=0}^j v_i \right|$$

over all  $0 \leq i \leq j < n$ .

It is possible to solve this in time  $O(n)$ :

It is possible to solve this in time  $O(n)$ :

```
1  int i = 0, j = 0;
2  int sum = v[0];
3  int best = sum;
4
5  while (i < n) {
6      best = min(best,abs(sum-k));
7      if (sum < k && j < n) {
8          j++;
9          sum += v[j];
10     }
11     else {
12         sum -= v[i];
13         i++;
14     }
15 }
```

Why this works (sketch):

- ▶ Say an interval is **interesting** if it has a chance to be optimal (given current knowledge).
- ▶ Suppose the current interval is  $[i, j]$  and suppose that all **unseen interesting intervals**  $[i', j']$  are such that  $i' \geq i$  and  $j' \geq j$ . (This is true when  $i = j = 0$ .)
- ▶ If  $\text{sum}([i, j]) > k$  then **all** unseen interesting intervals  $[i', j']$  have  $i' > i$ . So we set  $i = i + 1$ .
- ▶ If  $\text{sum}([i, j]) \leq k$  then **all** unseen interesting intervals  $[i', j']$  have  $j' > j$ . So we set  $j = j + 1$ .

## Trick/technique (Sliding window)

Some problems in which you need to find some **optimal interval** can be solved in linear time using a similar **sliding window** approach.

# Graph Traversals

## Storing graphs

If the graph is given explicitly, it is typically best to store it as an **adjacency list**. For example:

```
vector< vector<int> > adj(n);  
  
for (int i = 0; i < m; i++) {  
    int u, v;  
    cin >> u >> v;  
    adj[u].push_back(v);  
    adj[v].push_back(u);  
}
```



## Storing graphs

If the graph is given explicitly, it is typically best to store it as an **adjacency list**. For example:

```
vector< vector<int> > adj(n);  
  
for (int i = 0; i < m; i++) {  
    int u, v;  
    cin >> u >> v;  
    adj[u].push_back(v);  
    adj[v].push_back(u);  
}
```

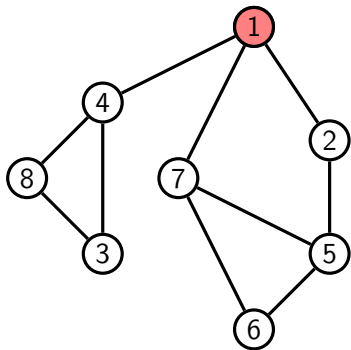
(this will be different when you start using the bgl)

## Storing graphs

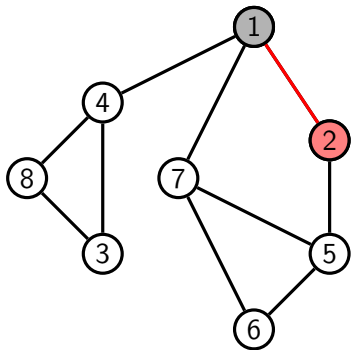
Often the graph is given **implicitly**, meaning that you can efficiently compute the neighbourhood of a given vertex.

- ▶ In this case, it is probably best **not** to store the graph in memory.

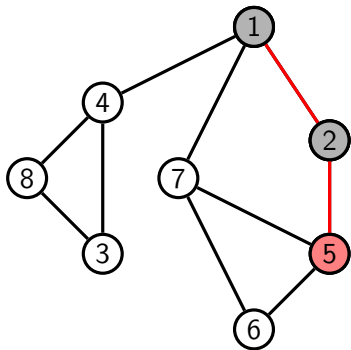
## Depth-first search



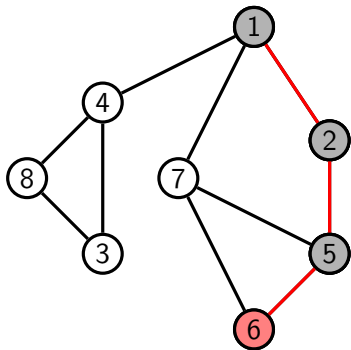
## Depth-first search



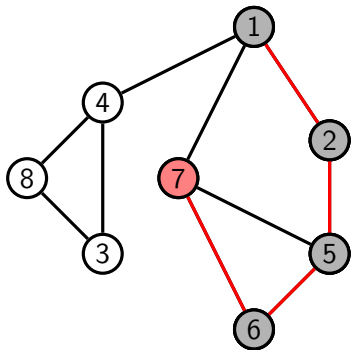
## Depth-first search



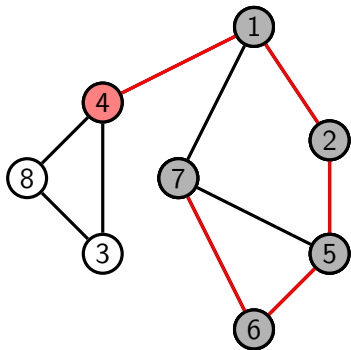
## Depth-first search



## Depth-first search

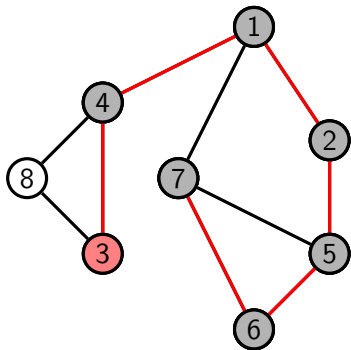


## Depth-first search

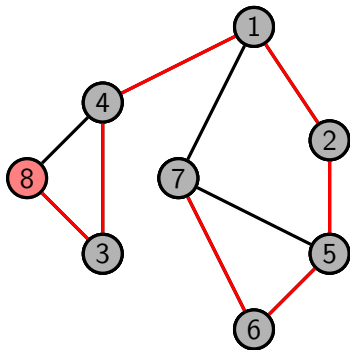




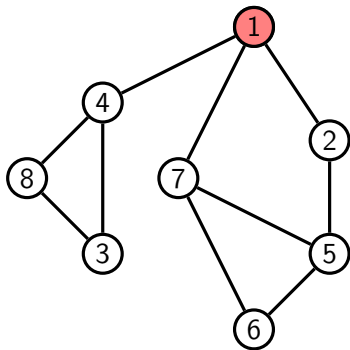
## Depth-first search



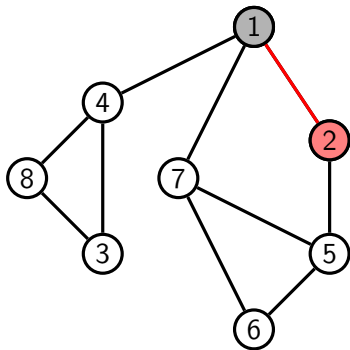
## Depth-first search



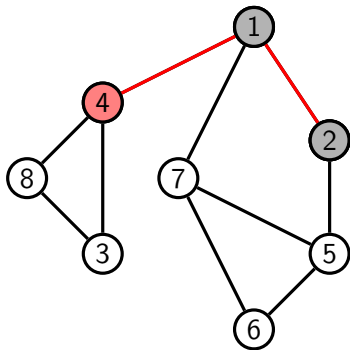
## Breadth-first search



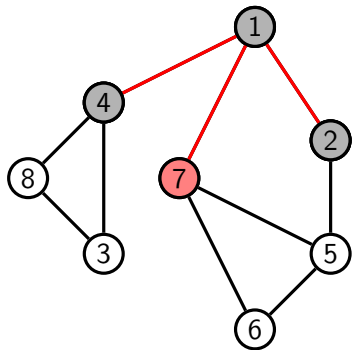
## Breadth-first search



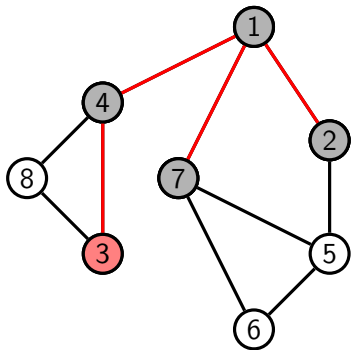
## Breadth-first search



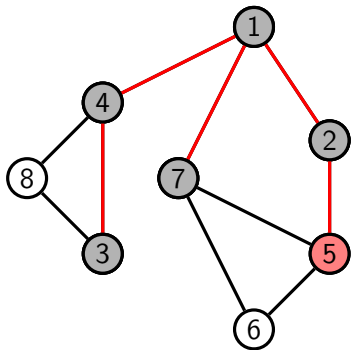
## Breadth-first search



## Breadth-first search

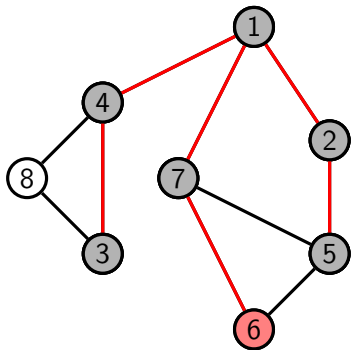


## Breadth-first search

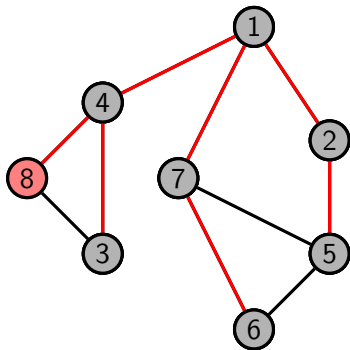




## Breadth-first search



## Breadth-first search



# Recurive DFS implementation

```
vector<int> visited(n, 0);

void dfs(int v) {
    // do something for v
    for (int u : adj[v]) {
        if (not visited[u]) {
            visited[u] = 1;
            dfs(u);
        }
    }
    // maybe do something else for v
}
```

## Correct BFS implementation

```
queue<int> q;  
vector<int> pushed(n, 0);  
  
q.push_back(v0);  
pushed[v0] = 1;  
  
while (not q.empty()) {  
    int v = q.front();  
    // do something for v  
    q.pop_front();  
    for (int u : adj[v]) {  
        if (not pushed[u]) {  
            q.push_back(u);  
            pushed[u] = 1;  
        }  
    }  
}
```

# Greedy Algorithms

- ▶ Often choices that seem best in a particular moment turn out not to be optimal in the long run (e.g., in chess, life, etc.).
- ▶ But sometimes **locally optimal** choices result in a **globally optimal** solution.
- ▶ This is when we can apply **greedy algorithms**.

A greedy approach typically has the following steps:

1. **Modeling**: realize that your task requires you to construct a set that is in some sense **globally optimal**.
2. **Greedy choice**: given already chosen elements  $c_1, \dots, c_{k-1}$ , decide how choose  $c_k$ , based on some **local optimality criterion**.
3. **Prove** that elements obtained in this way result in a **globally optimal** set.
4. **Implement** the greedy choice to be as efficient as possible.

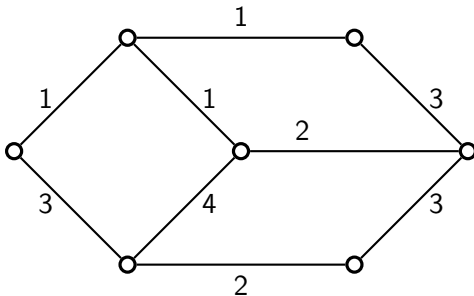
## Example (MST)

In a graph  $G$  with non-negative **edge weights**, find a **minimum weight spanning tree**.



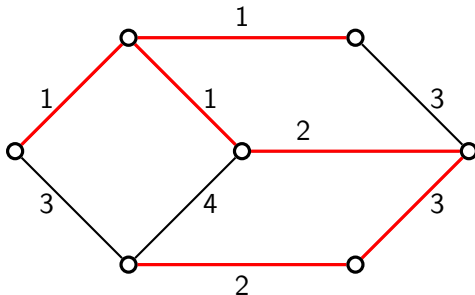
## Example (MST)

In a graph  $G$  with non-negative **edge weights**, find a **minimum weight spanning tree**.



## Example (MST)

In a graph  $G$  with non-negative **edge weights**, find a **minimum weight spanning tree**.



## Example: MST

First step: **model** as an optimization problem over sets.

In this case, we want to find a **set of edges** with minimum weight that forms a spanning tree.

## Example: MST

Second step: how to make the **greedy choice**.

Idea:

- ▶ suppose we already have edges  $e_1, \dots, e_{k-1}$
- ▶ choose  $e_k$  so that
  1. adding  $e_k$  to  $e_1, \dots, e_{k-1}$  does not close a cycle (**compatibility**)
  2.  $e_k$  has minimum weight among all compatible edges (**local optimality**)

## Example: MST

Third step: **prove** that this is correct.

### General method: exchange argument

- ▶ Let  $e_1, \dots, e_{n-1}$  be the choices made by the greedy algorithm.
- ▶ Let  $T$  be an optimal solution.
- ▶ If all edges  $e_1, \dots, e_{n-1}$  belong to  $T$ , we are done.
- ▶ Otherwise, suppose  $T$  contains  $e_1, \dots, e_i$ , but not  $e_{i+1}$ .
- ▶ Modify  $T$  to obtain an optimal solution containing  $e_1, \dots, e_{i+1}$ .

## Example: MST

Final step: **implement** the algorithm efficiently.

1. **Sort** the edges according to increasing weight.
2. Iterate over the edges in this order.
3. For each edge  $uv$ , if  $u$  and  $v$  are in the different components formed by the previous edges, add the edge to the MST.

To keep track of the components, use a **union find** data structure.

This takes time  $O(m \log m)$ .

This is **Kruskal's algorithm** for MST.

## Example (Interval scheduling)

- ▶ Your CPU needs to execute  $n$  jobs described by time intervals  $[s_i, f_i]$ .
- ▶ Job  $i$  starts at time  $s_i$  and ends at time  $f_i$ .
- ▶ Two jobs are **compatible** if their intervals are disjoint.
- ▶ **Goal**: find the maximum number of mutually compatible jobs.

## Example: Interval scheduling

**Modeling:** done for us in the problem description: find the maximum set of compatible jobs.



## Example: Interval scheduling

**Greedy choice:** decide how to choose the job  $j_k$  given already chosen jobs  $j_1, \dots, j_{k-1}$ .

Natural candidates:

- ▶ **Earliest start time** – among compatible jobs, take the one with smallest  $s_k$ .
- ▶ **Earliest finish time** – among compatible jobs, take the one with smallest  $f_k$ .
- ▶ **Shortest length** – among compatible jobs, take the one with smallest  $f_k - s_k$ .
- ▶ **Fewest conflicts** – among compatible jobs, take the one which conflicts with the least amount of other compatible jobs.

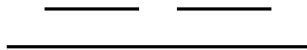
## Example: Interval scheduling

Earliest start time  
Earliest finish time  
Shortest length  
Fewest conflicts

Which one do you think will work?

## Example: Interval scheduling

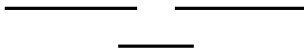
Earliest start time



Wrong

## Example: Interval scheduling

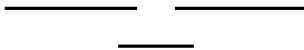
Shortest length



Wrong

## Example: Interval scheduling

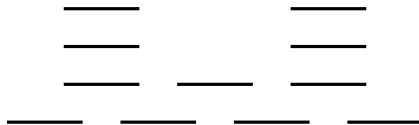
Shortest length



Wrong

## Example: Interval scheduling

Fewest conflicts



Wrong

## Example: Interval scheduling

Earliest finish time

???

## Example: Interval scheduling

Prove that earliest finish time is correct.

### General method: exchange argument

- ▶ Let  $j_1, \dots, j_N$  be the jobs chosen according to earliest finish time.
- ▶ Let  $J$  be a maximum set of jobs.
- ▶ If all jobs  $j_1, \dots, j_N$  belong to  $J$ , we are done.
- ▶ Otherwise, suppose  $J$  contains  $j_1, \dots, j_i$ , but not  $j_{i+1}$ .
- ▶ Modify  $J$  to obtain an optimal solution containing  $j_1, \dots, j_{i+1}$ .



## Example: Interval scheduling

Final step: **implement** the algorithm efficiently.

1. **Sort** the jobs according to increasing finish time.
2. Iterate over the jobs in this order.
3. For each job with interval  $[s_i, f_i]$ , add the job if  $s_i$  is greater than the finish time of the last job that was added.

This takes time  $O(n \log n)$ .

## Conclusion:

- ▶ Some (**but not all!**) problems can be solved with a greedy approach.
- ▶ Deciding how to make the greedy choice can be non-obvious.
- ▶ We can check whether the greedy solution works using an **exchange argument**.