### Shortest paths algorithms in weighted graphs

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## Shortest paths in weighted graphs

## Índex

- Reminder of basic graph definitions
- Oncatenation of paths
- Basic definitions on weighted graphs
- Shortest paths
- Optimal substructure of shortest paths
- **(**) Basic properties of shortest paths: triangle inequality
- **O** The routing problem: Single-source shortest paths

<sup>1</sup> A (combinatorial) graph is a pair G = (V, E) consisting of a set of vertices or nodes V, and a subset  $E \subset V \times V$  of the Cartesian product  $V \times V$ .

In the case of an *undirected graph* the elements of *E* are called *edges* and the pairs  $(a, b) \in E$  are considered unordered (that is, there is an edge between  $a \in V$  and  $b \in V$  when  $(a, b) \in E$  or  $(b, a) \in E$  — i.e., the pairs (a, b) and (b, a) are identified).

In the case of a *directed* or *oriented graph* the elements of *E* are called *arrows* and the pairs  $(a, b) \in E$  are considered with order (that is, there is an arrow from  $a \in V$  to  $b \in V$  if and only if  $(a, b) \in E$ , and the pairs (a, b) and (b, a) are *not* identified).

<sup>1</sup>http://en.wikipedia.org/wiki/Graph\_theory

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## Reminder of basic graph definitions (II)

- The *order* of a graph is the number of vertices, i.e. the *cardinal* of the set *V*: |*V*|.
- The *size* of a graph is the number of edges or arrows, i.e. the *cardinal* of the set *E*: *|E*|.
- The *degree* or *valence* of a vertex is the number of edges reaching or leaving the vertex (if an edge connects a vertex with itself it counts twice).
  - The *in-degree* of a vertex is the number of edges that arrive to the vertex.
  - The *out-degree* of a vertex is the number of edges coming out of the vertex.
- The vertices that belong to a single edge (i.e. the vertices of valence 1) are called *terminal* or *extreme* vertices.
- A vertex with valence larger than 2 is called a *branching vertex*.

## Reminder of basic graph definitions: paths and loops

- A *path* is a linear sequence of connecting edges. When the graph is oriented, the end of an arrow must be the beginning of the next one.
- The *length* of a path is the number of its edges or arrows.
- A *loop* or *circuit* is a closed path. That is, the end of the last edge coincides with the beginning of the first one.
- A path is called *acyclic* if it does not contain any circuit or loop. Observe that a path is cyclic if and only if it has repeated vertices. Equivalently, a path is acyclic if and only if every vertex appears only once in the path.

### Basic graph definitions: Concatenation

Given two paths

$$\alpha = (a_0 \longrightarrow a_1 \longrightarrow \cdots \longrightarrow a_n)$$
 of length  $n$ , and  
 $\beta = (b_0 \longrightarrow b_1 \longrightarrow \cdots \longrightarrow b_m)$  of length  $m$ ,

such that  $a_n = b_0$ , we define the *concatenation of*  $\alpha$  *and*  $\beta$ , denoted by  $\alpha\beta$ , as the path

$$\alpha\beta:=\big(a_0\to a_1\to\cdots\to a_n\to b_1\to\cdots\to b_m\big).$$

**Observation:** The length of  $\alpha\beta$  is n + m, i.e. the addition of lengths of  $\alpha$  and  $\beta$ .

Assume that  $\alpha$  is a loop (i.e.  $a_n = a_0$ ). In what follows we will use the following notation:

$$\alpha^{1} := \alpha,$$
  

$$\alpha^{2} := \alpha \alpha,$$
  

$$\alpha^{3} := \alpha^{2} \alpha = \alpha \alpha \alpha,$$
  

$$\cdots \qquad \cdots,$$
  

$$\alpha^{n} := (\alpha^{n-1}) \alpha = \overbrace{\alpha \alpha}^{n \text{ times}} \text{ for every } n \ge 2.$$

A *weighted graph*<sup>2</sup> or a *network* is a graph in which a number (the *weight*) is assigned to each edge (see the examples in Page 7). Such weights might represent for example costs, lengths or capacities, depending on the problem at hand.

Notationally the weight associated to and edge or arrow is usually written above the edge or the arrow.

Also, we can encompass all the weights of a graph in a single *edge-weight function*:

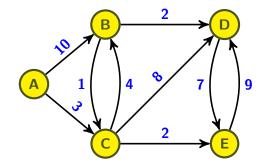


<sup>2</sup>A weighted graph can be both directed and undirected.

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## Basic definitions on weighted graphs





Example on the edge-weight function:  $\omega((C, D)) = 8$ .

### Basic definitions on weighted graphs

In a weighted graph, the *weight of path*  $\alpha = v_0 \longrightarrow v_1 \longrightarrow \cdots \longrightarrow v_n$  is defined to be

$$\omega(\alpha) := \sum_{i=1}^n \omega((\mathbf{v}_{i-1}, \mathbf{v}_i)).$$

Example (on the weighted graph at the right of Page 7)

Consider the following (weighted) path in the graph:

$$\alpha = A \xrightarrow{10} B \xrightarrow{1} C \xrightarrow{4} B \xrightarrow{2} D \xrightarrow{7} E.$$

Then 
$$\omega(\alpha) = 10 + 1 + 4 + 2 + 7 = 24.$$

### Observation

If  $\alpha\beta$  is a concatenated path then, clearly,

$$\omega(\alpha\beta) = \omega(\alpha) + \omega(\beta).$$

## Basic definitions on weighted graphs: shortest paths

The *minimum* or *optimum weight* of a path from *a* to *b* is defined as

$$\sigma(u, v) := \min\{\omega(\alpha) : \alpha \text{ is a path from } u \text{ to } v\}.$$

**Convention:**  $\sigma(u, v) = \infty$  if no path from *u* to *v* exists.

Important observation (see the example in the next page)

The minimum weight  $\sigma(u, v)$  of a path may not exist. However, when it exists it is uniquely defined.

A minimal path from  $u \in V$  to  $v \in V$  is any path from u to v with weight  $\sigma(u, v)$  (i.e. with minimum weight), whenever the minimum weight  $\sigma(u, v)$  exists.

### Observation: non-unicity of minimal paths

In general, there might be several minimal paths between a given pair of vertices.



## Basic definitions on weighted graphs: an example The minimum weight may not be well defined when there is a negative weight cycle

Consider the weighted graph at the right of Page 7 with  $\omega((C, B)) = 4$  replaced by  $\omega((C, B)) = -4$ . Consider also a family of paths

$$\alpha_n = (A \longrightarrow B) (B \longrightarrow C \longrightarrow B)^n (B \longrightarrow D \longrightarrow E)$$

with  $n \ge 1$ , similar to the ones from the previous example. Then,

$$\omega(\alpha_n) = \omega(A \longrightarrow B) + \omega((B \longrightarrow C \longrightarrow B)^n) + \omega(B \longrightarrow D \longrightarrow E)$$
$$= \omega(A \longrightarrow B \longrightarrow D \longrightarrow E) + n\omega(B \longrightarrow C \longrightarrow B)$$
$$= 19 - 3n.$$

The minimum weight  $\sigma(A, E)$  of a path from A to E is not defined since in the graph there are such paths of arbitrarily small (negative) weight, because

$$\lim_{n\to\infty}\omega(\alpha_n)=\lim_{n\to\infty}19-3n=-\infty.$$

#### Conclusion

All edge weights must be non-negative or, equivalently, the edge-weight function  $\omega$  is a function from E to  $\mathbb{R}^+$ :  $\omega: E \longrightarrow \mathbb{R}^+$ .

In the spirit of the previous page, a weighted graph  $(V, E, \omega)$  will be called

- *non-negative* whenever  $\omega(a) \ge 0$ ;
- positive if  $\omega(a) > 0$ ; and
- strongly positive if there exists  $\tau > 0$  such that  $\omega(a) \ge \tau$

### for every edge $a \in E$ .

The conclusion of the previous page is that the minimum weight (and hence the notion of optimal path) is only defined for non-negative weighted graphs. However, to assure the convergence of routing algorithms, for the single-source shortest paths problem, we will require that the graph is strongly positive.

## Basic properties of shortest paths: Optimal substructure

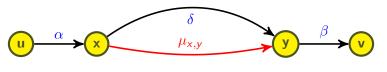
### Theorem (Optimality principle)

Any sub-path of a minimal path is minimal.

### Proof

Let  $\alpha\delta\beta$  be a minimal (concatenated) path from u to v, where  $\delta$  is a sub-path from x to y.

Assume by way of contradiction that  $\delta$  is not a minimal path from x to y. Then there exists a path  $\mu_{x,y}$  from x to y, such that  $\omega(\mu_{x,y}) < \omega(\delta)$  (in particular,  $\mu_{x,y} \neq \delta$ ). So,  $\alpha \mu_{x,y} \beta$  is another path from u to v such that  $\omega(\alpha \mu_{x,y}\beta) = \omega(\alpha) + \omega(\mu_{x,y}) + \omega(\beta) < \omega(\alpha) + \omega(\delta) + \omega(\beta) = \omega(\alpha\delta\beta)$ ; which contradicts the assumption that  $\alpha\delta\beta$  is a path from u to v of minimal weight.



## Basic properties of shortest paths: triangle inequality

### Theorem (Triangle Inequality)

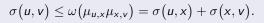
For all  $u, v, x \in V$ , we have  $\sigma(u, v) \leq \sigma(u, x) + \sigma(x, v)$ .

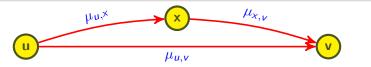
### Proof

Observe that if either does not exist path from u to x or from x to v, then  $\sigma(u, x) + \sigma(x, v) = \infty$ , and the lemma holds. Otherwise, let  $\mu_{u,x}$ be a minimal path from u to x (i.e.  $\omega(\mu_{u,x}) = \sigma(u,x)$ ), and let  $\mu_{x,v}$  be a minimal path from x to v (i.e.  $\omega(\mu_{x,v}) = \sigma(x, v)$ ). The concatenated path  $\mu_{u,x}\mu_{x,v}$  is clearly a path from u to v, and

$$\omega(\mu_{u,x}\mu_{x,v}) = \omega(\mu_{u,x}) + \omega(\mu_{x,v}) = \sigma(u,x) + \sigma(x,v).$$

Hence (by the definition of minimum weight)





## Statement of the routing problem: Single-source shortest paths

### The single-source shortest paths problem

Let  $(V, E, \omega)$  be a strongly positive weighted graph. Given a *source* vertex  $\xi \in V$ , find a minimal path and the optimum path weight from  $\xi$  to every node from V.

### The routing problem

Let  $(V, E, \omega)$  be a strongly positive weighted graph. Given a *source* vertex  $\xi \in V$  and a *goal* node<sup>3</sup>  $\gamma \in V$ , find a minimal path and the optimum path weight from  $\xi$  to  $\gamma$ .

The single-source shortest paths problem for standard (unweighted) graphs is usually formulated in a rooted graph, being the root the *source vertex*.

<sup>3</sup>The notation  $\xi \in V$  to denote the *source vertex*, and  $\gamma \in V$  for the *goal node* will be kept throughout the rest of the presentation.

## The single-source shortest paths problem for unweighted graphs: Breadth-first search

### The single-source shortest paths problem for unweighted graphs

Let (V, E) be an unweighted graph or, equivalently, let  $(V, E, \omega)$  be a weighted graph with constant weight function  $\omega$ ; i.e.  $\omega(a) = 1$  for every  $a \in E$ .

Given a *source* vertex  $\xi \in V$ , find a minimal path and the optimum path weight from  $\xi$  to every node from V.

As it is well known, this is equivalent to the computation of the *depths* of all nodes from a graph with the source node as *root*.

This problem can be solved in time O(|V| + |E|) by the *Breadth-first search algorithm* (by means of a FIFO queue). The BFS algorithm computes a *minimal spanning tree* of the graph.



Grafs: Definicions i Algorismes Bàsics, Pages 45 to 70, http://mat.uab.cat/~alseda/MatDoc/GrafsDefimovs.pdf

## Dijkstra's Algorithm

# Índex

- Introduction to Dijkstra's Algorithm
- ② Dijkstra's Algorithm in pseudocode
- Omments on Dijkstra's Algorithm
- Oijkstra's Algorithm and minimum spanning trees
- O An example of the Dijkstra's Algorithm
- **o** Implementation of the Dijkstra's Algorithm in **C**
- Onvergence of Dijkstra's Algorithm
- Analysis of Dijkstra's Algorithm efficiency

Dijkstra's algorithm is designed to solve the *single-source shortest paths problem* by computing a minimal spanning tree.

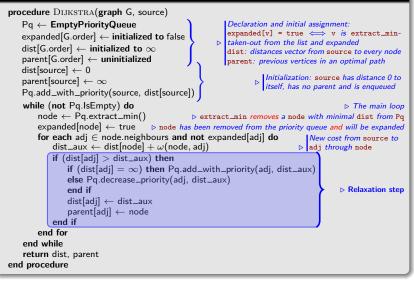
It can also solve the *routing problem* by stopping the algorithm once the shortest path to the destination node has been determined.

Dijkstra's algorithm is based on a (controlled) *greedy strategy*; that is, it makes a local optimal choice at every stage<sup>4</sup>.

<sup>4</sup>A greedy strategy does not usually produce an optimal solution by itself.

## Dijkstra's Algorithm

### Dijkstra's Algorithm for graphs, using an efficient priority queue



## Comments on Dijkstra's Algorithm

### dist[v] = $\infty$ for some vertex v

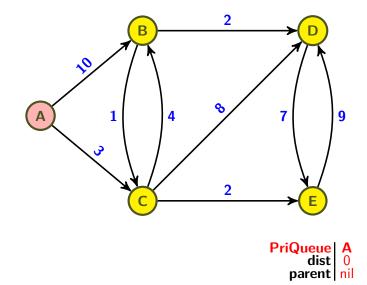
This will happen at termination whenever the vertex v is unreachable form the source. This may indicate that the graph is not connected or that it is directed and there is no (direct) path from the source vertex to v.

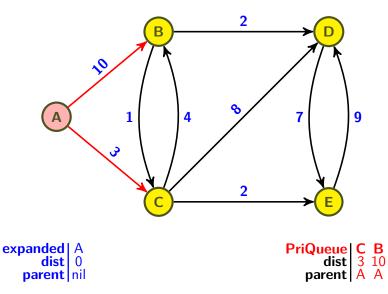
### How the minimal spanning tree is specified?

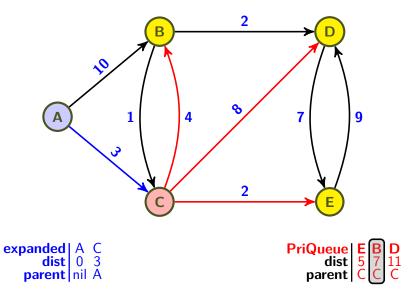
Through the vectors dist and parent.

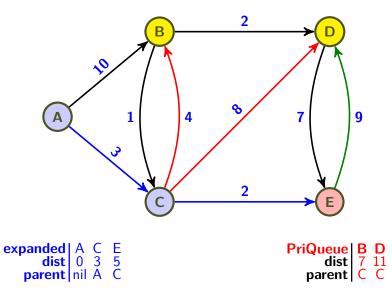
- dist[v] gives the computed optimal distance from source to the vertex v.
- parent[v] specifies the predecessor of the node v in a shortest path.

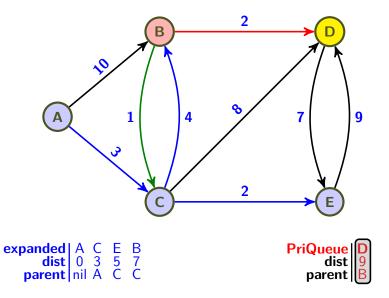
Thanks to the vector **parent** we can backwards construct the computed optimal paths to all vertices, thus building a minimal spanning tree.

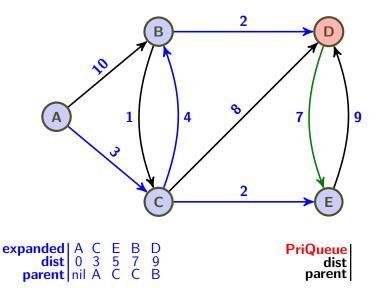


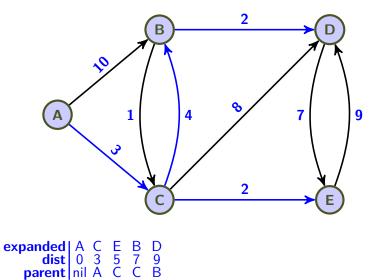












Lluís Alsedà Shortest paths algorithms in weighted graphs

#### Initializations and main

```
#include <stdio h>
#include <stdlib.h>
#include <values.h> // For MAXFLOAT = \infty and UINT MAX = \infty
                                                                       Output: the minimal spanning tree
                                                                           Vertex |
                                                                                   Cost | Parent
typedef struct{ unsigned vertexto; float weight; } weighted arrow;
typedef struct{ char name;
                unsigned arrows_num; weighted_arrow arrow[5];
                                                                           A (0) |
                                                                                     0.0
                                                                           B(1) \mid 7.0 \mid C(2)
               float dist; unsigned parent;
                                                                           C (2) |
                                                                                     3.0 \mid A(0)
} graph_vertex;
                                                                           D (3) |
                                                                                     9.0 | B (1)
                                                                           E (4) |
                                                                                     5.0 | C (2)
#define ORDER 5
int main() { register unsigned i;
    graph_vertex Graph[ORDER] = {
        { 'A', 2, {{1, 10}, {2, 3}}, MAXFLOAT, UINT_MAX }, // vertex 0
        { 'B', 2, {{2, 1}, {3, 2}}, MAXFLOAT, UINT MAX }, // vertex 1
       { 'C', 3, {{1, 4}, {3, 8}, {4, 2}}, MAXFLOAT, UINT_MAX }, // vertex 2
       { 'D', 1, {{4,7}}, MAXFLOAT, UINT_MAX }, // vertex 3
        { 'E', 1, {{3,9}}, MAXFLOAT, UINT_MAX }, // vertex 4
   1:
   Dijkstra(Graph, OU);
   fprintf(stdout, "Vertex | Cost | Parent\n------|------\n"):
   fprintf(stdout, " %c (%u) |%6.1f |\n", Graph[0].name, 0U, Graph[0].dist);
   for(i=1; i < ORDER; i++)</pre>
      fprintf(stdout, " %c (%u) |%6.1f | %c (%u)\n",
              Graph[i].name, i, Graph[i].dist, Graph[Graph[i].parent].name, Graph[i].parent);
```

Priority queue declarations and the Dijkstra function code

```
typedef struct QueueElementstructure {
   unsigned v;
   struct QueueElementstructure *seg:
} QueueElement:
typedef QueueElement * PriorityQueue;
int IsEmptv( PrioritvQueue Pa ){ return ( Pa == NULL ); }
void Dijkstra(graph_vertex * Graph, unsigned source){
    PrioritvQueue Pa = NULL:
    char expanded[ORDER] = \{[0, \dots, ORDER-1] = 0\}:
    Graph[source].dist = 0.0;
    add with priority(source, &Pg, Graph);
    while(!IsEmpty(Pq)){ register unsigned i;
        unsigned node = extract min(&Pa);
        expanded[node] = 1;
        for(i=0; i < Graph[node].arrows_num; i++){</pre>
            unsigned adj = Graph[node].arrow[i].vertexto;
            if(expanded[adi]) continue:
            float dist_aux = Graph[node].dist + Graph[node].arrow[i].weight;
            if(Graph[adi].dist > dist aux){
                char Is_adj_In_Pq = Graph[adj].dist < MAXFLOAT;</pre>
                Graph[adj].dist = dist_aux;
                Graph[adj].parent = node;
                if(Is_adj_In_Pq) decrease_priority(adj, &Pq, Graph);
                else add_with_priority(adj, &Pq, Graph);
```

The priority queue functions code: extract\_min

#### Notation and the definition of a Priority Queue

Given pointers QueueElement \*a, \*b, we will write a < b to denote that the queue element \*b is a descendant (in the queue) of the element \*a (that is,  $b = a -> seg -> seg \cdots -> seg$ ). In these notes a *Priority Queue* verifies

```
a < b \iff \texttt{Graph[a-v].dist} \leq \texttt{Graph[b-v].dist}
```

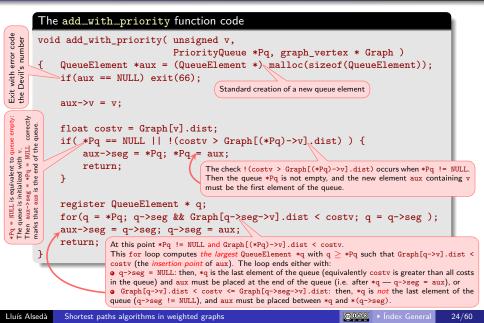
for every pair of valid pointers QueueElement \*a, \*b.

Then the function **extract\_min** has to deal (without any search) with the first element of the queue.

#### The extract\_min function code

```
unsigned extract_min(PriorityQueue *Pq){
  PriorityQueue first = *Pq;
  unsigned v = first->v;
  *Pq = (*Pq)->seg;
  free(first);
  return v;
}
```

The priority queue functions code: add\_with\_priority



The function requeue\_with\_priority code:

a simple but inefficient approach to decrease\_priority

#### Notation and Strategy

v->seg != NULL
is in the queue.

is not necessary to check prepv

since prepv is initialized as \*Pq, (\*Pq)->seg <= pv and v = prepv->seg->v is Then, in the loop, prepv->seg will run through the queue element containing v.

compute prepv: It

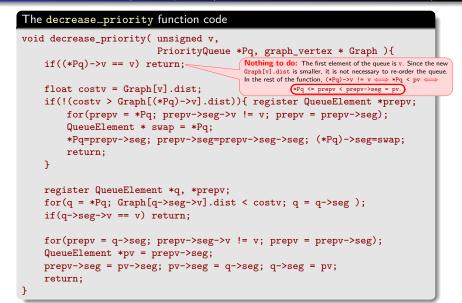
for loop to

```
pv denotes the pointer QueueElement * pv to the element of the queue which contains v. In particular, (pv->v = v.)
prepv denotes the pointer QueueElement * prepv to the element of the queue which is before *pv. That is, prepv->seg = pv, and (prepv->seg->v = pv->v = v.)
```

Strategy: Remove \*pv from the queue and re-enqueue v with the new decreased cost.

### The requeue\_with\_priority function code

The function decrease\_priority code (with detailed comments in the next pages)



Comments to the decrease\_priority function code The special case costv <= Graph[(\*Pq)->v].dist

The new cost costv of \*pv is smaller than or equal to the cost of \*Pq.

**Strategy:** \*pv has to be moved to the beginning of the queue

Consequently, we need to compute prepv and

```
connect *prepv with *(pv->seg) = *(prepv->seg->seg)
```

Remark: This justifies why we need to compute prepv instead of the (apparently more natural) computation of pv.

#### Computation of prepv (pv = prepv->seg)

```
As we have seen, here we have (*Pq) \rightarrow v! = v, which is equivalent to
```

```
*Pq <= prepv < prepv->seg = pv.
```

We can compute prepv with this for loop — see the "callout" note at page 25.

#### **Case:** !(costv > Graph[(\*Pq)->v].dist)

```
float costv = Graph[v].dist;
if(!(costv > Graph[(*Pq)->v].dist)){ register QueueElement *prepv;
    for(prepv = *Pq; prepv->seg->v != v; prepv = prepv->seg);
    QueueElement * swap = *Pg:
    *Pq=prepv->seg; prepv->seg=prepv->seg->seg; (*Pq)->seg=swap;
    return;
```

1

Comments to the decrease\_priority function code The general case costv > Graph[(\*Pq)->v].dist

The *new cost* costv of \*pv is larger than the cost of \*Pq.

#### Notation

In the general case, when the loop below stops, we have q >= \*Pq and Graph[a->v].dist < costv <= Graph[q->seg->v].dist for every QueueElement \*a such that \*Pq <= a <= q (see the corresponding "callout" note at page 24).

#### Strategy

Compute q and pv (in fact, prepv), and re-allocate \*pv = \*(prepv->seg) between \*q and \*(q->seg).

### Computation of q and exit if $q \rightarrow seg = pv$

```
register QueueElement *q, *prepv;

for(q = *Pq; Graph[q->seg->v].dist < costv; q = q->seg );

if(q->seg->v == v) return;
```

#### **Exercise:** if $(q \rightarrow seg \rightarrow v == v)$ there is nothing to do

When  $q \rightarrow seg \rightarrow v = v \iff q \rightarrow seg = pv$  it is not difficult to see that the queue is still sorted after decreasing Graph[v].dist.

From now on q->seg->v != v  $\iff$  q->seg != pv which implies q->seg < pv.

## Implementation of the Dijkstra's Algorithm in C

Final comments to the decrease\_priority function code

#### Strategy recalled

Compute q (already done) and prepv, and re-allocate \*pv = \*(prepv->seg) between \*q and \*(q->seg).

#### Computation of prepv

```
As we have seen, here we have q->seg < pv, which is equivalent to
q->seg <= prepv < prepv->seg = pv.
```

```
Then the for loop below sequentially computes prepv.
```

It is not necessary to check the condition prepv->seg != NULL (see the vertical "callout" note at page 25) because prepv is initialized as q->seg <= prepv and v = prepv->seg->v is in the queue. Then, in the loop, prepv->seg must run through the queue element containing v.

Computation of prepv and re-allocation of \*pv = \*(prepv->seg)

```
>for(prepv = q->seg; prepv->seg->v != v; prepv = prepv->seg);
QueueElement *pv = prepv->seg;
```

```
prepv->seg = pv->seg; pv->seg = q->seg; q->seg = pv;
```

return;

#### Re-allocation of \*pv = \*(prepv->seg) between \*q and \*(q->seg)

We also need to connect \*prepv with \*(pv->seg) = \*(prepv->seg->seg).

## Convergence of Dijkstra's Algorithm

The convergence of Dijkstra's Algorithm is assured by the next

#### Theorem

The equality dist[v] =  $\sigma(\text{source}, v)$  holds whenever a vertex  $v \in V$  is dequeued (with the function extract\_min) and expanded, and it is maintained during the rest of the algorithm. In particular, Dijkstra's algorithm terminates with dist[v] =  $\sigma(\text{source}, v)$  for every vertex  $v \in V$ .

To prove this theorem we will use the following two lemmas:

#### DA-Lemma 1

The inequality dist[v]  $\geq \sigma(\text{source}, v)$  holds at every iteration of the algorithm, for every vertex  $v \in V$ .

#### DA-Lemma 2

Let  $\alpha$  be a minimal path from source to a vertex  $v \in V$ . Let u be the predecessor of v in  $\alpha$ , and assume that dist[u] =  $\sigma$ (source, u). Then, if the edge (u, v) is relaxed we have dist[v] =  $\sigma$ (source, v) after the relaxation.

## Convergence of Dijkstra's Algorithm (II)

#### DA-Lemma 1

The inequality dist[v]  $\geq \sigma(\text{source}, v)$  holds at every iteration of the algorithm, for every vertex  $v \in V$ .

#### Proof of DA-Lemma 1

The initial assignment

```
\begin{array}{l} \text{dist}[] \leftarrow \textbf{initialized to} \\ \text{dist}[\text{source}] \leftarrow 0 \end{array}
```

guarantees that dist[v]  $\geq \sigma(\text{source}, v)$  holds for every vertex  $v \in V$  when the algorithm starts (before the while loop).

Now we will prove that these inequalities are maintained during the whole algorithm. Assume by way of contradiction that there exists a first vertex v for which dist[v] <  $\sigma$ (source, v). Let u be the vertex that caused dist[v] to change (by setting dist[v] = dist[u] +  $\omega(u, v)$  at a relaxation step). We have,

$$\begin{split} \operatorname{dist}[v] &< \sigma(\operatorname{source}, v) & \triangleright \operatorname{assumption} \\ &\leq \sigma(\operatorname{source}, u) + \sigma(u, v) & \triangleright \operatorname{triangle inequality} \\ &\leq \sigma(\operatorname{source}, u) + \omega(u, v) & \triangleright \operatorname{dist}[u] + \omega(u, v) & \models \operatorname{dist}[v]; & equal to the weight of a specific path \\ &\leq \operatorname{dist}[u] + \omega(u, v) = \operatorname{dist}[v]; & \triangleright \operatorname{dist}[v] < \sigma(\operatorname{source}, v) \end{split}$$

a contradiction.

## Convergence of Dijkstra's Algorithm (III)

#### DA-Lemma 2

Let  $\alpha$  be a minimal path from source to a vertex  $v \in V$ . Let u be the predecessor of v in  $\alpha$ , and assume that dist[u] =  $\sigma$ (source, u). Then, if the edge (u, v) is relaxed we have dist[v] =  $\sigma$ (source, v) after the relaxation.

#### Proof of DA-Lemma 2

The minimality of  $\boldsymbol{\alpha}$  and the Optimality Principle imply that

$$\sigma(\text{source}, v) = \omega(\alpha) = \sigma(\text{source}, u) + \omega(u, v).$$

Observe that when the value of dist[v] is modified by the algorithm, it decreases strictly. Assume that, at some step of the algorithm, dist[v]  $\leq \sigma(\text{source}, v)$ . By DA-Lemma 1 we have that dist[v] =  $\sigma(\text{source}, v)$  until the end of the algorithm. Thus, the lemma holds in this case.

Suppose now that  $dist[v] > \sigma(source, v)$  before the relaxation. We have,

$$dist[v] > \sigma(source, v) = \sigma(source, u) + \omega(u, v) = dist[u] + \omega(u, v).$$

Then, during the relaxation step the algorithm sets

dist[v] = dist[u] + 
$$\omega(u, v) = \sigma(\text{source}, v)$$
.

## Convergence of Dijkstra's Algorithm (IV)

### Theorem (Convergence of Dijkstra's Algorithm)

The equality dist[v] =  $\sigma(\text{source}, v)$  holds whenever a vertex  $v \in V$  is dequeued (with the function extract\_min) and expanded, and it is maintained during the rest of the algorithm. In particular, Dijkstra's algorithm terminates with dist[v] =  $\sigma(\text{source}, v)$  for every vertex  $v \in V$ .

### Proof of Theorem

If dist[v] =  $\sigma(\text{source}, v)$  holds whenever a vertex  $v \in V$  is dequeued, then this equality is maintained during the rest of the algorithm because of DA-Lemma 1 and the fact that the values dist[v] cannot increase during the computation.

So, we only need to prove the first statement of the theorem. Assume that  $v \in V$  is the first vertex for which the inequality  $dist[v] \neq \sigma(source, v)$  holds at the moment of dequeueing it with the function extract\_min. Note that, by DA-Lemma 1, in fact we have  $dist[v] > \sigma(source, v)$ .

Let us denote by S the set of vertices  $u \in V$  that have been already dequeued with the function extract\_min and expanded. Clearly,

- source  $\in S$ ,
- $v \notin S$  because the algorithm is just going to dequeue v, and
- since v is the first vertex that will be dequeued with  $dist[v] > \sigma(source, v)$ , the equality  $dist[u] = \sigma(source, u)$  holds for every vertex  $u \in S$  whenever it is dequeued, and it is maintained during the rest of the algorithm.

## Convergence of Dijkstra's Algorithm (V) Proof of the Theorem

## Proof of Theorem (continued)

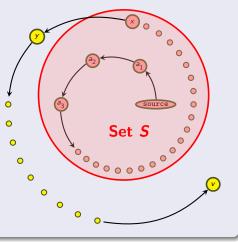
Let  $\beta$  be a minimal path from source to v. Since source  $\in S$ , there exist vertices  $x, y \in V$  such that:

- (1) (x, y) is an edge of  $\beta$ ,
- 2  $y \notin S$ , and
- every vertex lying in the sub-path of β from source to x (including x) belongs to S.

When the vertex x was dequeued and added to S, we had

dist  $[x] = \sigma(\text{source}, x)$ , and the edge (x, y) was relaxed. By DA-Lemma 2 with v replaced by y, u replaced by x, and  $\alpha$  replaced by the sub-path of  $\beta$  from source to y(notice that  $\alpha$  is a minimal path by the Optimality Principle), we get dist $[y] = \sigma(\text{source}, y)$ 

after the relaxation of (x, y).



### Proof of Theorem (end)

Since  $y \notin S$ , then either dist[y] =  $\infty > dist[v]$  (recall that every node in the queue has finite dist value), or y is in the queue and dist[v]  $\leq dist[y]$  because v is being dequeued with extract\_min.

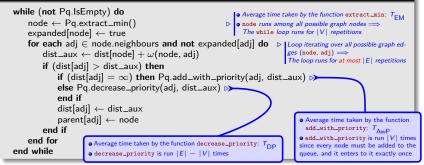
On the other hand, since v is farther from source than y in the minimal path  $\beta$ , we have  $\sigma(\text{source}, y) \leq \sigma(\text{source}, v)$ .

Then, summarizing,

dist[v]  $\leq$  dist[y] =  $\sigma$ (source, y)  $\leq \sigma$ (source, v) < dist[v];

a contradiction.

# Dijkstra's Algorithm for graphs, using a priority queue Repetitive part — omitting initialization



#### Estimated average execution time

$$|V| (T_{\text{EM}} + T_{\text{AWP}}) + (|E| - |V|) T_{\text{DP}}$$

#### Table of estimated average run times for several Dijkstra's Algorithm functions

Queue strategy	T <sub>EM</sub>	T_AwP	T <sub>DP</sub>	Total	Order
State Vector boolean	$\mathcal{O}\left(\frac{ V }{2}\right)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}\left( V ^2+ E  ight)$	$O( V ^2)$
Plain linked list not sorted	$\mathcal{O}\left(\frac{\overline{Q}}{2}\right)$	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}\left(\frac{ V \overline{Q}}{2} +  E \right)$	$\mathcal{O}\left( V \overline{Q}\right)$
Linked list sorted by priority	$\mathcal{O}(1)$	$\mathcal{O}\left(\frac{\overline{Q}}{2}\right)$	$\mathcal{O}\left(\frac{\overline{Q}}{2}\right)$	$\mathcal{O}\left( V  +  E \frac{\overline{Q}}{2}\right)$	$\mathcal{O}\left( E \overline{Q}\right)$
Binary Heap sorted by priority	$\mathcal{O}(1)$	$\mathcal{O}\left(\log_2\left(\overline{Q}\right)\right)$	$\mathcal{O}\left(\log_2\left(\overline{Q}\right)\right)$	$\mathcal{O}\Big( V + E \log_2\Big(\overline{Q}\Big)\Big)$	$\mathcal{O}\left( E \log_2\left(\overline{Q}\right)\right)$

Where  $\overline{Q}$  denotes the average number of elements in the queue during the whole algorithm.

#### Remarks

- For the computation of the the estimates for the worst case scenarios:  $\overline{Q} \leq |V|$  and  $|E| \in \mathcal{O}(|V|^2)$ .
- Boolean State Vector is a vector of type IsNodeInQueue[order] (of size order): A node v is in the queue if and only if IsNodeInQueue[v] = true. This strategy, when the graph is big, wastes a lot of memory and really gives a "worst case scenario".

In the next pages one can find detailed justifications of the above estimated average run times.

Justification of the estimated average run times

In the next computations we set n = |V| and we denote by  $Q_i$  the number of elements in the queue for the repetition *i* of the while loop, with i = 1, 2, ..., n. Also, we denote by  $d_i$  (respectively  $a_i$ ) the total number of times that the function decrease\_priority (respectively add\_with\_priority) has been run at the repetition *i* of the while loop.

**Observe that:** 
$$\sum_{i=1}^{n} d_i = |E| - n$$
 and  $\sum_{i=1}^{n} a_i = n$ .

Average run time of extract\_min for a plain linked list not sorted:

The expected run time  $T_{\text{EM}}$  at the repetition *i* of the while loop is  $\mathcal{O}\left(\frac{Q_i}{2}\right)$ . Thus, the total run time average is:

$$\frac{1}{n}\sum_{i=1}^{n}K_{i}\frac{Q_{i}}{2}\leq\frac{\max\{K_{1},K_{2},\ldots,K_{n}\}}{2}\frac{1}{n}\sum_{i=1}^{n}Q_{i}=\max\{K_{1},K_{2},\ldots,K_{n}\}\frac{\overline{Q}}{2}=\mathcal{O}\left(\frac{\overline{Q}}{2}\right).$$

Justification of the estimated average run times

Average run time of add\_with\_priority for a linked list sorted by priority:

The expected run time  $T_{AwP}$  at the repetition *i* of the while loop is  $O\left(\frac{Q_i}{2}\right)$ . The total run time average is:

$$\frac{1}{n}\sum_{i=1}^{n} \left( K_{j_1} + K_{j_2} + \dots + K_{j_{a_i}} \right) \frac{Q_i}{2} \le K \frac{1}{2n} \sum_{i=1}^{n} Q_i = \mathcal{O}\left(\frac{\overline{Q}}{2}\right)$$

Average run time of decrease\_priority for a linked list sorted by priority:

The expected run time  $T_{\text{DP}}$  at the repetition *i* of the while loop is  $\mathcal{O}\left(\frac{Q_i}{2}\right)$ . The total run time average is:

$$\frac{1}{|E|-n}\sum_{i=1}^n \left(K_{j_1}+K_{j_2}+\cdots+K_{j_{d_i}}\right)\frac{Q_i}{2} \leq \frac{Kn}{|E|-n}\frac{1}{2n}\sum_{i=1}^n Q_i = \mathcal{O}\left(\frac{\overline{Q}}{2}\right).$$

Justification of the estimated average run times

#### Average run time of add\_with\_priority for a binary heap sorted by priority:

The expected run time  $T_{AwP}$  at the repetition *i* of the while loop is  $\mathcal{O}(\log_2(Q_i))$ . Since the  $\log_2$  function is concave, by Jensen's Inequality we have that the total run time average is:

$$\frac{1}{n}\sum_{i=1}^{n} \left( \mathcal{K}_{j_{1}} + \mathcal{K}_{j_{2}} + \dots + \mathcal{K}_{j_{a_{i}}} \right) \log_{2}(Q_{i}) \leq \mathcal{K} \frac{1}{n}\sum_{i=1}^{n} \log_{2}(Q_{i}) \stackrel{\text{Jensen Ineq.}}{\leq} \mathcal{K} \log_{2}\left(\overline{Q}\right) \in \mathcal{O}\left(\log_{2}\left(\overline{Q}\right)\right).$$

#### Average run time of decrease\_priority for a binary heap sorted by priority:

The expected run time  $T_{\text{DP}}$  at the repetition *i* of the while *loop* is  $\mathcal{O}(\log_2(Q_i))$ . Since the  $\log_2$  function is concave, by *Jensen's inequality* we have that the total run time average is:

$$\begin{split} \frac{1}{|E|-n} \sum_{i=1}^n \Big( \mathcal{K}_{j_1} + \mathcal{K}_{j_2} + \dots + \mathcal{K}_{j_{d_i}} \Big) \log_2(Q_i) \leq \\ \frac{\mathcal{K}n}{|E|-n} \frac{1}{n} \sum_{i=1}^n \log_2(Q_i) \overset{\text{Jensen Ineq.}}{\leq} \mathcal{K} \log_2\left(\overline{Q}\right) \in \mathcal{O}\left(\log_2\left(\overline{Q}\right)\right). \end{split}$$

## A\* Algorithm

# Índex

- Introduction to A\* Algorithm
- A\* Algorithm pseudocode
- Omments on the A\* Algorithm
- An example of the A\* Algorithm
- Implementation of the A\* Algorithm in C
- **O** Algorithmic properties of A\*: Technical results
- Ø Algorithmic properties of A\*: Termination and Completeness
- 8 Algorithmic properties of A\*: Admissibility
- Algorithmic properties of A\*: Dominance and Optimality
- Algorithmic properties of A\*: Monotone (Consistent) Heuristics
- Algorithmic properties of A\*: Properties of Monotone Heuristics

## Introduction to A<sup>\*</sup> Algorithm<sup>5</sup>

A<sup>\*</sup> is a graph traversal and path search algorithm for solving the *routing problem*. It is *complete*, *optimal* and *computationally efficient*. It is the best solution in many cases (despite of the major practical drawback that it stores all generated nodes in memory).

 $A^*$  is an *informed search algorithm*, or a *best-first search*. It maintains a tree of paths originating at the start node and extending one edge at a time until its termination criterion is satisfied.  $A^*$  can be seen as an extension of Dijkstra's Algorithm. It achieves better performance by using heuristics to guide its search.

At each iteration of its main loop,  $A^*$  needs to determine which of its paths to extend. It does so based on the cost of the path and an estimate of the cost required to extend the path all the way to the goal. Specifically,  $A^*$  selects the path that minimizes f(v) = g(v) + h(v) where v is the next node on the path, g(v) is the cost of the path from the start node to v, and h(v) is a heuristic function that estimates the cost of the cheapest path from v to the goal.

 $\mathsf{A}^{\star}$  terminates when the path it chooses to extend is a path from start to goal or if there are no paths eligible to be extended.

<sup>5</sup>Inspired in https://en.wikipedia.org/wiki/A\*\_search\_algorithm

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## Introduction to A<sup>\*</sup> Algorithm

The heuristic function<sup>6</sup> is problem-specific. When it is *admissible*, meaning that it never overestimates the actual cost to get to the goal,  $A^*$  is guaranteed to return a least-cost path from start to goal.

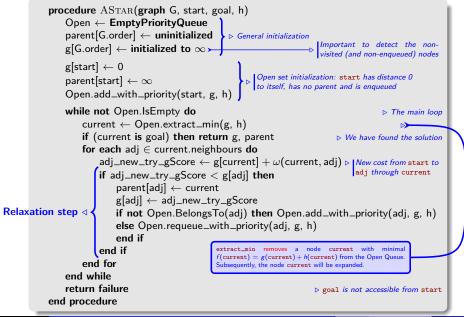
Typical implementations of  $A^*$  use a *priority queue* to perform the repeated selection of minimum (estimated) cost nodes to expand. This priority queue is known as the *Open Queue* (or *Open Set*). At each step of the algorithm, the node with the lowest f value is removed from the queue, the f and g values of its neighbours are updated accordingly, and these neighbours are added to the queue. The algorithm continues until a removed node (thus the node with lowest f value out of all open nodes) is a goal node. The f value of that goal is then also the cost of the shortest path, since h at the goal is zero in an admissible heuristic.

To find the actual sequence of steps that constitute a shortest path, as in Dijkstra's Algorithm, one has to keep track of the predecessor of each node on the computed shortest path. At  $A^*$  termination, the ending node will point to its predecessor, and so on, until some node's predecessor is the start node.



<sup>&</sup>lt;sup>6</sup>As an example, when searching for the shortest route on a map, h(v) might represent the straight-line distance from v to the goal, since that is physically the smallest possible distance between any two points.

## A\* Algorithm pseudocode



## The A\* Philosophy

### $A^{\star}-Remark$

Let  $v \in V$  be a vertex of G for which there exists a node  $u \in V \setminus \{\gamma\}$  such that:

- (u, v)  $\in E$  is an edge of the graph,
- u is removed from the Open Queue by the function extract\_min, and

$$g(v) > g(u) + \omega(u, v).$$

Then, the if clause of the relaxation step holds true for adj = v, and

- g(v) is set to the lower value  $g(u) + \omega(u, v) < \infty$ ,
- *u* is set to be parent[v], and
- v is set to belong to the Open Queue with the new g(v) value.

Moreover, this is the only way that v can enter to the Open Queue and parent[v] can be modified.

### Definition

The operation described in the above remark will be called *relaxing the* node v after expanding the node u.



## The A\* Philosophy: Another view of A\*

The basic operative of the A $^*$  Algorithm is based on the construction (exploration) of paths in the following sense:

#### Definition

Let  $\alpha := (v_0 \longrightarrow v_1 \longrightarrow \cdots \longrightarrow v_{n-1} \longrightarrow v_n)$  be a path in the graph *G*. We say that  $\alpha$  has been *constructed by the A*<sup>\*</sup> *Algorithm* if, at some of the A<sup>\*</sup> iterates,  $v_n$  is relaxed after the expansion of  $v_{n-1}$ ,  $g(v_i) < \infty$  for  $i = 0, 1, \ldots, n$ , and  $v_j = \texttt{parent}[v_{j+1}]$  for  $j = 0, 1, \ldots, n-1$ .

Then, a basic result about the A\* Algorithm that complements the A\*–Remark is the following:

#### A\* Basic Lemma

All paths constructed by the  $A^*$  Algorithm are acyclic.

A consequence of the A<sup>\*</sup> Basic Lemma is that the basic operative of the A<sup>\*</sup> Algorithm constructs a subset of the acyclic paths strating at  $\xi$ , and traverses the subgraph of *G* formed by the union of these acyclic paths.

## The A<sup> $\star$ </sup> Philosophy: Another view of A<sup> $\star$ </sup> — Proofs

#### Remark (the A\* implemented path information does not allow cyclic paths)

The A\* (and Dijkstra) strategy of constructing backwards the shortest paths, which is based on keeping track of the predecessor (parent[]) of each node on the computed shortest path, can never give as a result a cyclic path because every node can have a unique parent.

Thus, the implemented way of constructing the shortest paths (fortunately) agrees with the previous lemma.

#### Proof of A\* Basic Lemma

Assume that  $A^*$  has just constructed a cyclic path  $(x_0 \longrightarrow x_1 \longrightarrow \cdots \longrightarrow x_k)\alpha$ , where  $\alpha := (v_0 \longrightarrow v_1 \longrightarrow \cdots \longrightarrow v_{n-1} \longrightarrow v_n)$  is a loop (i.e.,  $v_n = v_0$ ). Without loss of generality we may assume that  $\alpha$  is acyclic (i.e.,  $v_0, v_1, \ldots, v_{n-1}$  are pairwise different). Then, prior to the relaxation of  $v_n$  after the expansion of  $v_{n-1}$  the nodes  $v_0 = \text{parent}[v_1], v_1 = \text{parent}[v_2], \ldots, v_{n-2} = \text{parent}[v_{n-1}]$  and  $v_{n-1}$  have been previously relaxed. Thus, by A\*-Remark,

$$g(v_0) = g(v_n) > g(v_{n-1}) + \omega(v_{n-1}, v_n) = g(v_{n-2}) + \omega(v_{n-2}, v_{n-1}) + \omega(v_{n-1}, v_n) = \cdots = g(v_0) + \sum_{i=0}^{n-1} \omega(v_i, v_{i+1}) > g(v_0);$$

a contradiction.

## On the heuristic function

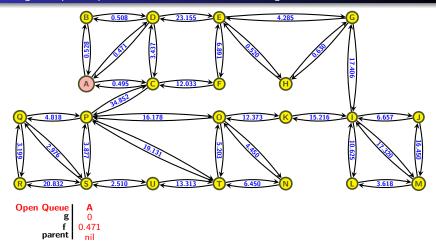
It is clearly seen that the whole algorithm and, in particular, its efficiency depend on the heuristic function.

As we will see, the best heuristic function is the one that estimates (but never overestimates) the actual cost to get to the goal.

### Example

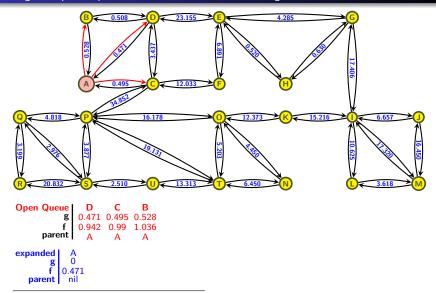
Let  $G = (V, E, \omega)$  be a weighted graph and let  $\gamma$  denote the goal node. For every vertex  $v \in V$  we set  $h(v) := \begin{cases} \min\{\omega(v, u) : (v, u) \in E\} & \text{if } v \neq \gamma, \\ 0 & \text{if } v = \gamma. \end{cases}$ 

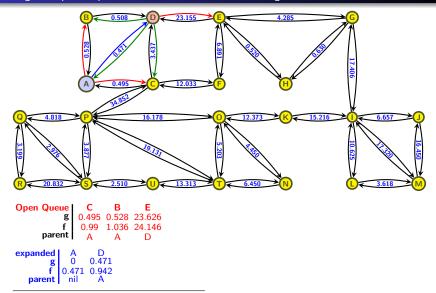
We will show that the heuristic function in this example is *admissible* and *monotone*, but it is a bad since is far from correctly estimating  $\sigma(\mathbf{v}, \gamma)$ .

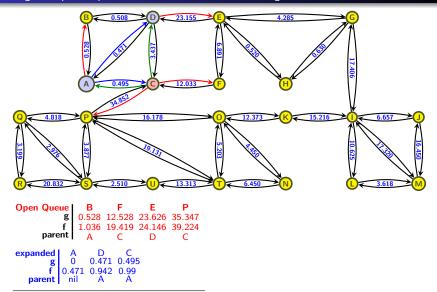


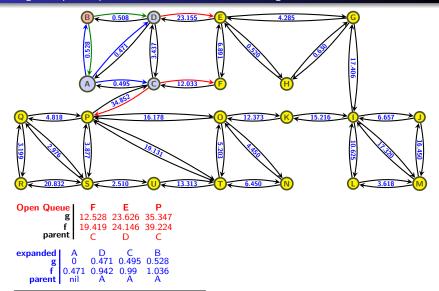


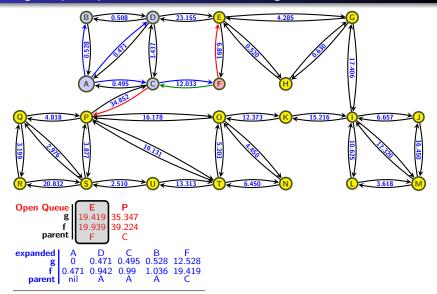
Observe that the *f*-values of the expanded nodes are non-decreasing and there is no re-opened node (to be expanded again), as prescribed by the fact that the heuristic is monotone.

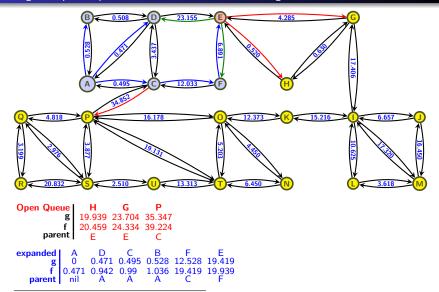


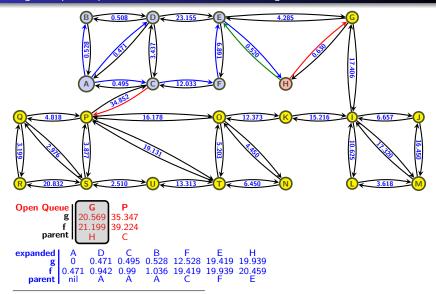


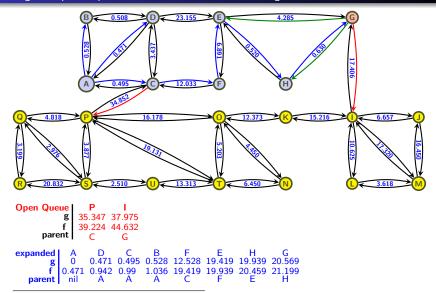


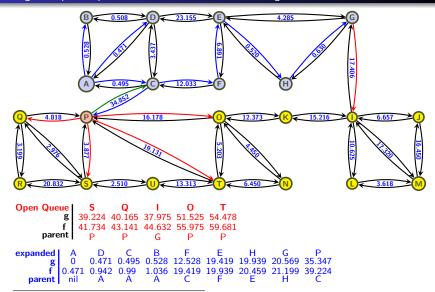


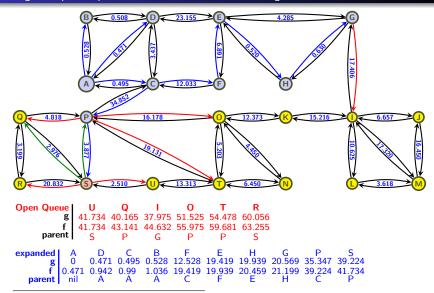


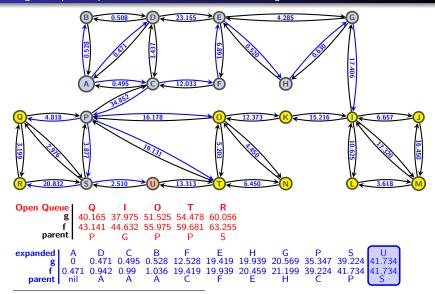












Declarations and auxiliary functions

#### Graph declarations and auxiliary functions

```
typedef char bool; enum {false, true};
typedef struct{ unsigned vertexto; float weight; } weighted_arrow;
typedef struct{ char name; unsigned arrows_num; weighted_arrow arrow[5]; } graph_vertex;
typedef struct { float g; unsigned parent; } AStarPath;
```

bool AStar(graph\_vertex \*, AStarPath \*, unsigned, unsigned, unsigned);

```
void ExitError(const char *miss, int errcode) {
   fprintf (stderr, "\nERROR: %s.\nStopping...\n\n", miss); exit(errcode);
```

#### Priority Queue and $\mathtt{A}^\star$ declarations and auxiliary functions

```
typedef struct QueueElementstruct { unsigned v; struct QueueElementstruct *seg; } QueueElement;
typedef QueueElement * PriorityQueue;
typedef struct { float f; bool IsOpen; } AStarControlData;
```

float heuristic(graph\_vertex \*Graph, unsigned vertex, unsigned goal){ register unsigned short i; if(vertex == goal) return 0.0; float minw = Graph[vertex].arrow[0].weight; for(i=1; i < Graph[vertex].arrow\_num ; i++){ if(Graph[vertex].arrow[i].weight < minw ) minw = Graph[vertex].arrow[i].weight; } return minw; } Question

Is the heuristic function a good one? If not, how to improve it?

To implement the function Open.BelongsTo() efficiently in time

Instead of sequentially explore the whole queue to determine whether a given node v belongs to the list, it is much simpler to check if ASCD[v].IsOpen is true. The drawback is that this bool variable costs one byte more per node, and its maintenance must be done manually (add\_vith\_priority automatically sets this variable for easiness).

### main program and results

#define GraphOrder 21	Output: Shortest path						
<pre>int main() {   graph_vertex Graph[GraphOrder] = {     {'A', 3, { {1, 0.528}, {2, 0.495}, {3, 0.471} }},     {'B', 2, { {0, 0.528}, {3, 0.508} },    </pre>	Node name   Distance A (000)   Source C (002)   0.495 P (015)   35.347 S (018)   39.224 U (020)   41.734						
<pre>bool r = AStar(Graph, PathData, GraphOrder, node_start, node_goal); if(r == -1) ExitError("in allocating memory for the OPEN list in AStar", 21); else if(!r) ExitError("no solution found in AStar", 7); register unsigned v=node_goal, pv=PathData[v].parent, ppv; PathData[node_goal].parent=UINT_MAX; while(v != node_start) { ppv=PathData[v].parent; PathData[pv].parent=v; v=pv; pv=pv; } printf("Optimal path found:\nNode name   Distance\n\n"); printf(" %c (%3.3u)   Source\n", Graph[node_start].name, node_start);</pre>							
<pre>for(v=PathData[node_start], parent; v !=UINT_MAX; v=PathData[v].parent) printf(" %c (%3.3u)   %7.3f\n", Graph[v].name, v, PathData[v].g); return 0; }</pre>							
Starting at node_goal, reverse the parents path so that successor becomes parent and, conversely, parent becomes successor. Then, we can write the optimal path forward; starting at node_start until we arrive at node_goal.							

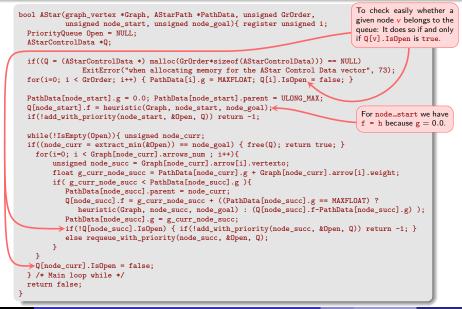
### main program and results

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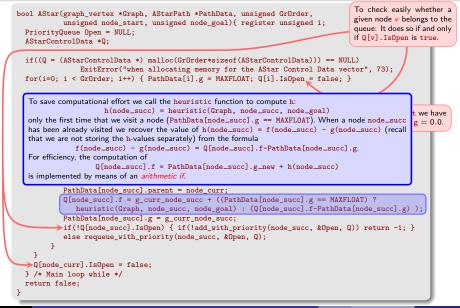
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#define GraphOrder 21	Output: Shortest path						
<pre>int main() {   graph_vertex Graph[GraphOrder] = {     {'A', 3, { {1, 0.528}, {2, 0.495}, {3, 0.471} }},     {'B', 2, { {0, 0.528}, {3, 0.508} },    </pre>	Node name   Distance A (000)   Source C (002)   0.495 P (015)   35.347 S (018)   39.224 U (020)   41.734						
<pre>bool r = AStar(Graph, PathData, GraphOrder, node_start, node_goal); if(r == -1) ExitError("in allocating memory for the OPEN list in AStar", 21); else if(!r) ExitError("no solution found in AStar", 7); register unsigned v=node_goal, pv=PathData[v].parent, ppv; PathData[node_goal].parent=UINT_MAX; while(v != node_start) { ppv=PathData[v].parent; PathData[pv].parent=v; v=pv; pv=pv; } printf("Optimal path found:\nNode name   Distance\n\n"); printf(" %c (%3.3u)   Source\n", Graph[node_start].name, node_start);</pre>							
<pre>for(v=PathData[node_start], parent; v !=UINT_MAX; v=PathData[v].parent) printf(" %c (%3.3u)   %7.3f\n", Graph[v].name, v, PathData[v].g); return 0; }</pre>							
Starting at node_goal, reverse the parents path so that successor becomes parent and, conversely, parent becomes successor. Then, we can write the optimal path forward; starting at node_start until we arrive at node_goal.							

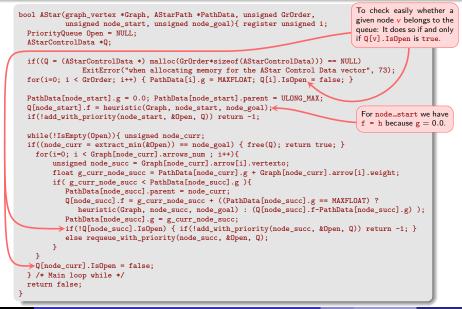
#### The Dijkstra function code



#### The Dijkstra function code



#### The Dijkstra function code



## Implementation of the A<sup>\*</sup> Algorithm in C

Priority queue functions code — Alike Dijkstra's algorithm

```
bool IsEmptv(PrioritvQueue Pa){
                                   void requeue with_priority(unsigned v, PriorityQueue *Pq,
 return ((bool) (Pq == NULL));
                                                               AStarControlData * Q){
                                     register QueueElement * prepv:
unsigned extract min(
                                     if((*Pq) \rightarrow v == v) return:
          PriorityQueue *Pq){
 PrioritvQueue first = *Pa;
                                     for(prepv = *Pq; prepv->seg->v != v; prepv = prepv->seg);
 unsigned v = first -> v:
                                     QueueElement * pv = prepv->seg;
                                     prepv->seg = pv->seg;
 *Pq = (*Pq)->seg;
                                     free(pv);
 free(first):
 return v: }
                                   add_with_priority(v, Pq, Q); }
bool add with priority(unsigned v, PriorityQueue *Pq, AStarControlData * Q){
    register QueueElement * a:
    QueueElement *aux = (QueueElement *) malloc(sizeof(QueueElement));
    if(aux == NULL) return false;
    aux -> v = v:
   float costv = Q[v].f;
   Q[v].IsOpen = true:
    if( *Pq == NULL || !(costv > Q[(*Pq)->v].f) ) {
        aux \rightarrow seg = *Pq; *Pq = aux;
        return true:
    £
    for(q = *Pq; q->seg && Q[q->seg->v].f < costv; q = q->seg ) ;
    aux->seg = g->seg; g->seg = aux;
    return true;
```

## Algorithmic properties of A\*:

Termination and Completeness

#### Theorem

A\* always terminates on finite graphs.

### Remark (finiteness of acyclic paths starting at $\xi$ )

Let C be the maximal subgraph of G that contains  $\xi$  and is connected. Observe that every path of G starting at  $\xi$  is contained in C.

Let  $m_{\xi}$  denote the out-degree of  $\xi$  in *C*, let *m* denote the maximum out-degree of a vertex in *C*, and let  $\ell$  denote the number of vertices in *C* (including  $\xi$ ).

Since a path is acyclic if and only if every vertex appears at most once in the path, the length of an acyclic path starting at  $\xi$  is smaller than or equal to  $\ell - 1$ . So, the number of acyclic paths starting at  $\xi$  can be brutally upper bounded by  $m_{\xi} \cdot m^{\ell-2}$ .

#### Proof

If A<sup>\*</sup> does not stop after finding a solution (by extracting  $\gamma$  from the Open Queue with the function extract\_min) then, by A<sup>\*</sup> Basic Lemma and the above Remark, it will traverse the subgraph of G formed by the union of finitely many acyclic paths starting at  $\xi$  in finite time. Upon completion of this traversal, the Open Queue will become empty and A<sup>\*</sup> will stop with failure.



An algorithm is said to be *complete* if it terminates with a solution when one exists.

### Completeness Theorem

 $A^*$  is complete (even on infinite graphs).

## Algorithmic properties of A\*: Admissibility

### Admissibility

An algorithm is *admissible* if it is guaranteed to return an optimal solution whenever a solution exists.

### Definition

An heuristic function *h* is said to be *admissible* if for every vertex  $v \in V$ ,

 $h(\mathbf{v}) \leq \sigma(\mathbf{v}, \gamma)$ 

where  $\gamma$  is the goal node.

Admissibility Theorem

A\* is admissible.

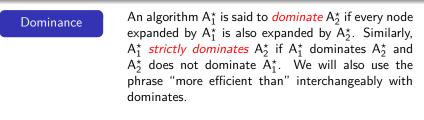
### Example (the heuristic function from Page 48 is admissible)

If  $v = \gamma$  we have:  $h(v) = h(\gamma) = 0 \le \sigma(v, \gamma)$ . If  $v \ne \gamma$ , let  $\alpha$  be an optimal path from v to the node goal  $\gamma$  and let  $u \in V$  be such that  $(v, u) \in E$  and  $\alpha$  starts with (v, u). We have

 $h(v) = \min\{\omega(v, x) : (v, x) \in E\} \le \omega(v, u) \le \omega(\alpha) = \sigma(v, \gamma).$ 

## Algorithmic properties of A\*:

Dominance and Optimality



Optimality

An algorithm is said to be *optimal* over a class of algorithms if it dominates all members of that class.

#### Definition

An heuristic function  $h_2$  is *more informed than*  $h_1$  if both are admissible and  $h_2(v) > h_1(v)$  for every non-goal vertex  $v \in V$ . Similarly, an A<sup>\*</sup> algorithm using  $h_2$  is said to be *more informed than* that using  $h_1$ .

#### Theorem

If  $A_2^*$  is more informed than  $A_1^*$ , then  $A_2^*$  dominates  $A_1^*$ .

## Algorithmic properties of A\*: Monotone (Consistent) Heuristics

By the triangle inequality we have  $\sigma(u, \gamma) \leq \sigma(u, v) + \sigma(v, \gamma)$  for every  $u, v \in V$ , where  $\gamma \in V$  denotes the goal node. Since, by admissibility  $h(\cdot)$  is an estimate of  $\sigma(\cdot, \gamma)$ , it is now reasonable to expect that if the process of estimating  $h(\cdot)$  is consistent, it should inherit the above inequality and satisfy  $h(u) \leq \sigma(u, v) + h(v)$  for every  $u, v \in V$ .

### Definition (Consistency and Monotonicity)

An heuristic function h is said to be *consistent* if  $h(u) \le \sigma(u, v) + h(v)$ is satisfied for all pairs of nodes  $u, v \in V$ .

A heuristic function h is said to be *monotone* if it satisfies  $h(u) \le \omega(u, v) + h(v)$ for every  $u, v \in V$  such that  $(u, v) \in E$  is an edge of the graph.

### Algorithmic properties of A\*: Monotone (Consistent) Heuristics

Monotonicity may seem, at first glance, to be less restrictive than consistency, because it only relates the heuristic of a node to the heuristics of its immediate successors. However, a simple proof by induction on the depth of the descendants of u shows the following

#### Theorem

A heuristic function is monotone if and only if it is consistent.

It is also simple to relate consistency to admissibility.

#### Theorem

Every consistent heuristic is admissible.

#### Example (the heuristic function from Page 48 is monotone)

Let  $u, v \in V$  be such that  $(u, v) \in E$  is an edge of the graph. Then,

$$h(u) = \min\{\omega(u, x) : (u, x) \in E\} \le \omega(u, v) \le \omega(u, v) + h(v)$$

because h is non-negative.

### Algorithmic properties of A<sup>\*</sup>: **Properties of Monotone Heuristics**

### $\xi \in V$ denotes the source node

### Theorem (All discovered paths are optimal)

An  $A^*$  algorithm guided by a monotone heuristic finds optimal paths to all expanded vertices  $v \in V$ . That is,

$$g(\mathbf{v}) = \sigma(\xi, \mathbf{v})$$

for every expanded vertex  $v \in V$ .

#### Theorem (Monotonicity of the sequence of f values)

Monotonicity implies that the sequence  $\{f(v_i)\}_{i=1}^{\ell}$  of f values of the sequence of vertices  $\{v_i\}_{i=1}^{\ell}$  expanded by A<sup>\*</sup> is non-decreasing.

#### Theorem (Easy expansion conditions)

If h is a monotone heuristic, then the necessary condition for expanding a vertex  $v \in V$  is given by

$$\sigma(\xi, \mathbf{v}) + h(\mathbf{v}) \leq \sigma(\xi, \gamma),$$

and the sufficient condition by the strict inequality  $\sigma(\xi, \mathbf{v}) + h(\mathbf{v}) < \sigma(\xi, \gamma).$