

Scheduling Problem with Greedy Solution

Setting:

- ▶ a number of **customers**, waiting to be served
- ▶ only **one** customer can be served at a given time
- ▶ it takes time $T(j)$ to serve customer j

Goal (as all customers equally important):

minimize sum of waiting times

Optimal Strategy:

if $T(j) < T(k)$ then serve j before k

Proof of optimality:

- ▶ consider a schedule S **not** following that strategy
- ▶ in S , there are two jobs j and k such that
 - ▶ j comes just before k
 - ▶ but $T(k) < T(j)$
- ▶ Hence S can be **improved**, by swapping j and k .
- ▶ Thus S is **not** optimal.

Greedy Algorithms

We saw a **Greedy** algorithm for the scheduling problem:

- ▶ it needs **not** explore search spaces, or backtrack
- ▶ but it knows **where to set its foot next**.

Many problems, but **not all**, allow **greedy** solutions; the proof of **correctness** often argues

*a schedule **not** following strategy can be improved*

but observe that **local** optima are **not** necessarily **global**:

*a schedule not improvable by “local” changes may still **not** be optimal*

Example: list the numbers $1..n$ so as to **minimize** sum of **neighbor distances**, where the distance between i and j is

$$\min(|i - j|, 5)$$

An optimal listing is $1..n$ (or $n..1$), with cost $n - 1$. But

6 7 8 9 10 1 2 3 4 5

is **not** optimal but swapping **two** numbers makes it **worse**.

Event Scheduling

Setting:

- ▶ **one** server which can host only **one** event at a time
- ▶ some **events**, each with **fixed start** & **finish** time

Goal (as all events equally important):

***maximize** the **number** of events allocated*

Attempts at **greedy** strategy:

1. prioritize the **shortest** events
2. prioritize the events with **fewest overlaps**

For each strategy, there is a **counterexample** that shows that it is **not** always optimal

Event Scheduling with Greedy Solution

Recall **Setting**:

- ▶ **one** server which can host only **one** event at a time
- ▶ some **events**, each with **fixed start** & **finish** time

Goal:

maximize the number of events allocated

Greedy strategy:

prioritize events that finish early

there is **no counterexample** as **correctness** can be proven:

- ▶ if $E_1..E_n$ is valid schedule
- ▶ and $E'_1..E'_m$ follows strategy
- ▶ then $m \geq n$ and E'_n will not finish later than E_n .

Another **correct greedy** strategy is the **symmetric**:

prioritize events that start late

Thus **scheduling order** may **not** equal **execution order**

Minimum-Cost Spanning Tree

Setting:

- ▶ **un**directed **connected** graph $G = (V, E)$
- ▶ where each edge has a **weight** > 0

a **Spanning Tree** is a **subset** E_0 of E that

- ▶ **spans**: each $v \in V$ is end point of some edge in E_0
- ▶ is a **tree**: (V, E_0) is acyclic and connected

Goal: find spanning tree with **minimum** total weight

- ▶ all spanning trees have $|V| - 1$ edges
- ▶ there may be many spanning trees
- ▶ and even more than one minimum-cost spanning tree

We shall present **two greedy** algorithms for finding **one** minimum-cost spanning tree.

Select an Edge with No Regret

Common Strategy: build minimal spanning tree by

- ▶ adding one edge at a time
- ▶ such that we will never regret our choice.

With T_0 the current edges, we can inductively assume
 T_0 can be extended to a minimum spanning tree.

When can an edge e be added to T_0 with no regret?

- ▶ suppose the nodes can be partitioned into 2 or more components with all edges in T_0 intra-component
- ▶ let E' be the inter-component edges
(observe that $E' \neq \emptyset$ and $T_0 \cap E' = \emptyset$).

Lemma:

- ▶ if $e \in E'$ and no other edge $\in E'$ has smaller weight
- ▶ then it is safe to add e to T_0 , in that $T_0 \cup \{e\}$ can be extended to a minimum-cost spanning tree.

Proof: lecture notes

Kruskal's algorithm

Kruskal's algorithm builds tree T_0 piecemeal:

- ▶ we keep track of connectivity components wrt T_0
- ▶ thus all edges in T_0 are intra-component
- ▶ and it is safe to add an inter-component edge with lowest weight.

Accordingly, Kruskal's algorithm first sorts the edges with lowest weight first, and then for each edge e :

- ▶ checks if its end points are in different components
- ▶ if so, it adds e to T_0

Running time (with $n = |V|$ and $a = |E|$):

1. sorting of edges: $\Theta(a \lg(a)) = \Theta(a \lg(n))$
2. we must a times check if two nodes are in different components, and if so merge those components; by union-find trees each can be done in time $O(\lg n)$.

Thus the total running time is in $\Theta(a \lg(n))$.

Prim's algorithm

Prim's algorithm lets the tree T_0 grow from a **single** node

- ▶ the nodes in T_0 form one **component**
- ▶ all other nodes form another component

To find an **inter**-component edge with **lowest** weight, we thus need for **each** node w **not** in T_0 to keep track of

*the minimum weight of an edge from w to a node in T_0 ,
together with one such edge, called $e(w)$*

To implement that, at least two feasible approaches:

- ▶ **priority queue** of nodes, where w has high priority if $e(w)$ has low weight
- ▶ **no** priority queue; instead rely on **linear search**.

Prim's algorithm, Running time Analysis

Two operations contribute to the total cost:

1. find & extract w with minimum $e(w)$:

- ▶ with linear search: in $\Theta(n)$
- ▶ with priority queue: in $\Theta(\lg n)$

number of times this is done: $\Theta(n)$

2. update $e(w)$ when u added to T_0 and there is edge (u, w) :

- ▶ with linear search: in $\Theta(1)$
- ▶ with priority queue: in $\Theta(\lg n)$

number of times this is done: a

Thus the total running time is

- ▶ with linear search: $\Theta(n^2 + a) = \Theta(n^2)$
- ▶ with priority queue: $\Theta(n \lg(n) + a \lg(n)) = \Theta(a \lg(n))$

Single Source Shortest Paths

Given a **directed** graph where edges have **length**, find
*the **smallest** total length of a path from s to u*

- ▶ for **specific** source s
- ▶ for **each** node u

This can be accomplished through **Dijkstra's algorithm**.

- ▶ while negative cycles would make no sense
- ▶ edges with **negative** length
 - ▶ can be handled by Floyd's algorithm
 - ▶ but **not** by Dijkstra's algorithm

There are algorithms (such as Bellman-Ford) for single source shortest paths that do allow negative lengths, but they are generally slower than Dijkstra's.

Dijkstra's Algorithm

Dijkstra's algorithm uses

- ▶ a table d that maps each node to a number ≥ 0
- ▶ a subset S of the nodes

and maintains the **invariant**:

1. if $v \in S$ then $d[v]$ is the **smallest** length of a path from the source to v (and there will be a path of that length where all nodes belong to S)
2. if $v \notin S$ then $d[v]$ is the smallest length of a path from the source to v where **all** nodes **but** v are in S

Key insight:

- ▶ if $d[v]$ is minimum among nodes not in S
- ▶ then it is safe to add v to S
(this relies on lengths not being negative)

Dijkstra's Algorithm, Initialization

Recall the **invariant**:

1. if $v \in S$ then $d[v]$ is the **smallest** length of a path from the source to v (and there will be a path of that length where all nodes belong to S)
2. if $v \notin S$ then $d[v]$ is the smallest length of a path from the source to v where **all** nodes **but** v are in S

which is **established** by

$S \leftarrow \emptyset$

foreach node X

if X is the source

$d[X] \leftarrow 0$

else

$d[X] \leftarrow \infty$

Dijkstra's Algorithm, Main Loop

Recall the **invariant**:

1. if $v \in S$ then $d[v]$ is the **smallest** length of a path from the source to v (and there will be a path of that length where all nodes belong to S)
2. if $v \notin S$ then $d[v]$ is the smallest length of a path from the source to v where **all** nodes **but** v are in S

which is **maintained** by

```
while there is a node  $\notin S$ 
  let  $Y \notin S$  be a node with  $d[Y]$  minimal
   $S \leftarrow S \cup \{Y\}$ 
  foreach edge  $Y \xrightarrow{q} Z$  with  $Z \notin S$ 
    if  $d[Y] + q < d[Z]$ 
       $d[Z] \leftarrow d[Y] + q$ 
      record: path to  $Z$  is thru  $Y$ 
```

In **1st** iteration, Y will be the source.

Dijkstra's Algorithm, Running Time

The analysis is as for **Prim's** algorithm:

1. to find & extract Y with minimum $d(Y)$:

- ▶ with linear search: in $\Theta(n)$
- ▶ with priority queue: in $\Theta(\lg n)$

number of times this is done : $\Theta(n)$

2. update $d(Z)$ when Y with edge $Y \rightarrow Z$ added to S :

- ▶ with linear search: in $\Theta(1)$
- ▶ with priority queue: in $\Theta(\lg n)$

number of times this is done: $\Theta(a)$

Thus the **total running time** is

- ▶ with **linear search**: $\Theta(n^2 + a) = \Theta(n^2)$
- ▶ with **priority queue**: $\Theta(n \lg(n) + a \lg(n)) = \Theta(a \lg(n))$

	Dijkstra's algorithm	differs from Prim's:
graph is	directed	undirected
computes	shortest paths	minimum spanning tree
maintains	distance from source	distance to current tree

Single/All Shortest Path

Source	Target	Algorithm	Running Time
Single	All	Dijkstra's	$\Theta(a \lg(n))$ or $\Theta(n^2)$
All	Single	Dijkstra's (reverse edges)	$\Theta(a \lg(n))$ or $\Theta(n^2)$
All	All	Floyd's n times Dijkstra's	$\Theta(n^3)$ $\Theta(an \lg(n))$ or $\Theta(n^3)$
Single	Single	Dijkstra's (early exit?)	NOT $\Theta(n)$

Fractional Knapsack

Recall the general **knapsack problem**:

- ▶ n items; each item i has **weight** w_i and **value** v_i
- ▶ **weight limit** (capacity) of W

Goal: find $x_1..x_n$ that

- ▶ satisfies $\sum_{i=1}^n x_i w_i \leq W$
- ▶ **maximizes** $\sum_{i=1}^n x_i v_i$

We have already looked at the **binary** version:
each x_i is either 0 or 1

We shall now consider the **fractional** version:
*each x_i is a **real** number with $0 \leq x_i \leq 1$.*

Which version is easier to solve?

- ▶ the binary can be solved by **brute force**
- ▶ the fractional **cannot** be solved by brute force
- ▶ but ...

Fractional Knapsack, Greedy Solution

Consider the example, with $W = 100$:

i	1	2	3	4	5
w	10	20	30	40	50
v	20	30	66	40	60

We may give priority to items with

1. higher value: $x = (0, 0, 1, 0.5, 1)$ giving 146
2. lower weight: $x = (1, 1, 1, 1, 0)$ giving 156
3. higher $\frac{v_i}{w_i}$: $x = (1, 1, 1, 0, 0.8)$ giving 164

Assessment:

- Strategies 1 and 2 are **not** always optimal
- Strategy 3 is indeed **always optimal** (proof in notes)

Is strategy 3 optimal also in the binary setting?

*no, as showed by simple counterexample
where we are forced to take "too much"*

Binary Encodings of Alphabets

We want to transmit **sequences of symbols** where each symbol α comes with a **frequency** $F(\alpha)$. **Example:**

α	a	b	c	d
$F(\alpha)$	0.4	0.1	0.3	0.2

An **encoding** B maps each symbol into a bit string, allowing us to encode a sequence of symbols:

$$B(\alpha_1.. \alpha_n) = B(\alpha_1)..B(\alpha_n)$$

Goal: find B that for **random** sequence s produces **minimum expected length** of $B(s)$

Naive approach: **Fixed length** encoding, such as

α	a	b	c	d
$B(\alpha)$	00	01	10	11

If $|s| = n$ then $|B(s)| = 2n$

Optimal Encodings of Alphabets

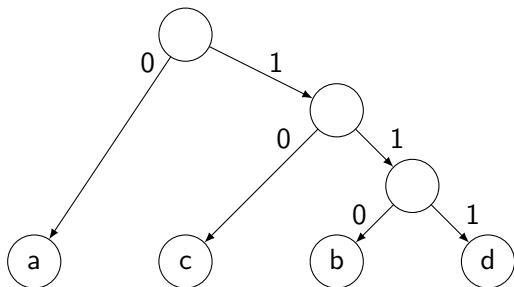
Variable length encoding:

α	a	b	c	d
$F(\alpha)$	0.4	0.1	0.3	0.2
$B(\alpha)$	0	110	10	111

If $|s| = n$ then we may **expect** $|E(s)|$ to be:

$$1 \cdot 0.4n + 3 \cdot 0.1n + 2 \cdot 0.3n + 3 \cdot 0.2n = 1.9n$$

To avoid **ambiguity**, no code has another code as prefix and thus B can be represented as **binary tree**:



Greedy Algorithm for Optimal Encoding

Huffman's algorithm:

1. initially, each symbol α forms a singleton tree, with frequency $F(\alpha)$
2. in each step, find trees t_1 and t_2 with $F(t_1)$, $F(t_2)$ **minimal**, and form tree t with t_1 and t_2 as children, and with $F(t) = F(t_1) + F(t_2)$

To prove **optimality**, a key observation is:

- ▶ if T is an optimal encoding
- ▶ then there exists (another) optimal encoding T' where the two least frequent symbols are siblings.