

# ISyE 7203: Logistics and System Engineering

Rui Gong

September 16, 2025

## Acknowledgements

These notes are based on the ISyE 7203 lectures given by Professor *Alejandro Toriello* in Fall 2025 at Georgia Institute of Technology.

## Contents

<b>1</b>	<b>Introduction</b>	<b>4</b>
1.1	Network Flows . . . . .	4
1.2	Shortest Path . . . . .	6
1.3	Shortest Path on Direct Acyclic Networks . . . . .	9
1.3.1	(Deterministic) Dynamic Programming (finite state, action, horizon) . . . . .	10
1.4	Max Flow . . . . .	10
1.4.1	Max Flow Applications . . . . .	11
<b>2</b>	<b>Traveling Salesman Problem</b>	<b>12</b>
2.1	TSP . . . . .	12
2.2	Approximate LP . . . . .	14
2.3	TSP Heuristic . . . . .	15
2.3.1	Minimum Spanning Tree(MST) Heuristic for Symmetric TSP . . . . .	15
2.3.2	Greedy Heuristics . . . . .	16

# 1 Introduction

## 1.1 Network Flows

### Definition 1.1

A network (graph) is made of the following:

- $(N)$  nodes (vertices): a finite set.
- For undirected network:  $(E)$  edges:  $\{i, j\}, i, j \in N$  drawn as  $i - j$ .
- For directed network:  $(A)$  arcs  $(i, j), i, j \in N$  drawn as  $i \rightarrow j$ , where we call  $i$  the tail and  $j$  the head of the arc.

For this course, we focus on the directed networks and the following definitions are all on directed networks.

### Definition 1.2

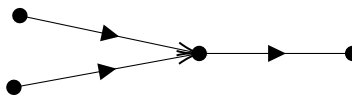
- path: a sequence of arcs where the head of the first is the tail of the second and so forth, and no nodes repeat.
- walk: a sequence of arcs where the head of the first is the tail of the second and so forth, and nodes may repeat.
- cycle: a path except that the first and the last nodes are the same. If a cycle has repeated nodes in between, it is a closed walk instead.

### Definition 1.3: Connectedness

A directed network is:

- strongly connected: for any  $i, j \in N$ , there exists an  $i \rightarrow j$  (directed) path and a  $j \rightarrow i$  directed path.
- weakly connected: for any  $i, j \in N$ , there exists an (undirected)  $i - j$  path if we ignore orientations.

Example 1.1. Consider the following network:



It is weakly but not strongly connected.

**Definition 1.4: network flow**

Given the network by  $(N, A)$ ,  $b \in \mathbb{R}^N$ ,  $c \in \mathbb{R}^A$ ,  $u \in (\mathbb{R} \cup \{\infty\})^A$ .  $b$  represents the net supply where  $i$  is a supplier, consumer, trans-shipment respectively if  $b_i > 0$ ,  $b_i < 0$ ,  $b_i = 0$  respectively;  $c$  represents the cost, and  $u$  represent the capacity.

For modeling,  $X_{ij}$  is used to represent the amount of flow on  $(i, j) \in A$ . Then the network flow problem is:

$$\begin{aligned} \min \quad & \sum_{a \in A} c_a x_a \\ \text{s.t.} \quad & \sum_{a \in \delta^+(i)} x_a - \sum_{a \in \delta^-(i)} x_a = b_i, i \in N \\ & 0 \leq x_a \leq u_a, \forall a \in A \end{aligned} \quad (\text{NF})$$

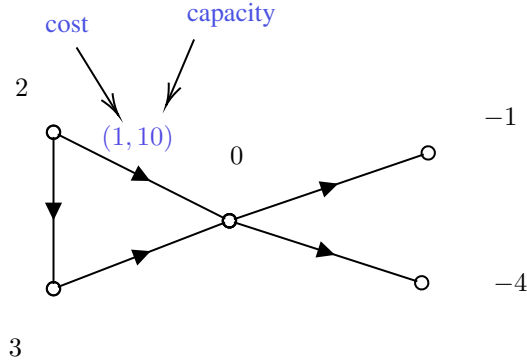
where  $\delta^+(i)$  is the set of arcs having  $i$  as the tail and  $\delta^-(i)$  is the set of arcs having  $i$  as the head. The equality constraints are called the flow balance constraint.

*Remark.* Aggregate the flow balance constraints, we get

$$\sum_i \left( \sum_{a \in \delta^+(i)} x_a - \sum_{a \in \delta^-(i)} x_a \right) = \sum_{a \in A} x_a - x_a = 0 = \sum_i b_i.$$

Thus,  $\sum_{i=1}^N b_i = 0$  is a needed assumption.

*Example 1.2.* The following is an instance of a network flow problem:

**Theorem 1.5**

The constraint matrix of (NF) is always TU (totally unimodular). Thus, if  $b, u$  are integral, all extreme points are integral.

*Example 1.3 (Assignment Problem).* Considering assigning  $n$  workers to  $n$  tasks, one for each. Let  $c_{ij}$  be the cost of assigning worker  $i$  to task  $j$ . In this way, we can consider  $1, \dots, n$  nodes as workers and  $n+1, \dots, 2n$  as tasks. For each node representing a worker, it has arcs from it to all task nodes. The supply of each worker and task are 1 and

−1 respectively. Then the problem can be written as:

$$\begin{aligned}
 \min \quad & \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ij} \\
 \text{s.t.} \quad & \sum_{j=n+1}^{2n} x_{ij} = 1, \quad i = 1, \dots, n \\
 & \sum_{i=1}^n -x_{ij} = -1 \\
 & 0 \leq x_{ij}.
 \end{aligned}$$

Notice that there is no need to have  $x_{ij} \leq 1$ , it is implied by the balance flow constraints and nonnegative constraints.

*Remark.* Indeed, the above example shows that the extreme points of the set of double stochastic matrices are permutation matrices.

*Example 1.4 (Transportation Problem).* Given suppliers  $i = 1, \dots, m$  with  $b_i$  units of supply and consumers  $j = 1, \dots, n$  with  $d_j$  units of demand, let  $c_{ij}$  be the cost per unit from  $i$  to  $j$ . Assume that  $\sum_i b_i = \sum_j d_j$ , then we get the LP:

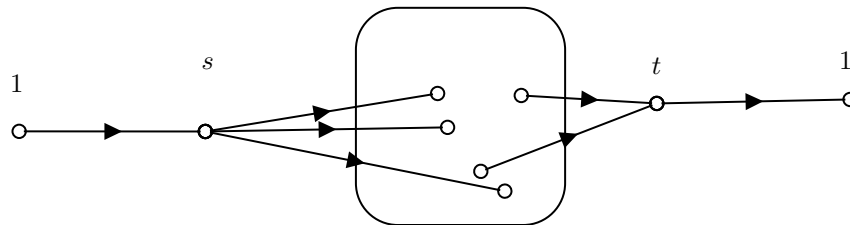
$$\begin{aligned}
 \min \quad & \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ij} \\
 \text{s.t.} \quad & \sum_{j=n+1}^{2n} x_{ij} = b_i, \quad i = 1, \dots, m \\
 & \sum_{i=1}^n -x_{ij} = d_j, \quad j = 1, \dots, n \\
 & 0 \leq x_{ij} \leq u_{ij}.
 \end{aligned}$$

What if  $\sum_i b_i > \sum_j d_j$ ?

We can consider adding a dummy customer whose demand is  $\sum_i b_i - \sum_j d_j$ . That is, we require a dummy customer takes all the extra supply.

## 1.2 Shortest Path

Given a directed network  $(N, A)$ , and  $s, t \in N, c \in \mathbb{R}^A$ . Goal: cheapest  $s - t$  path,

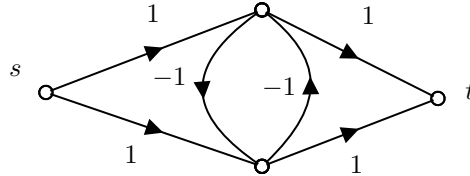


$$\begin{aligned}
 \min \quad & \sum_{a \in A} c_a x_a \\
 \text{s.t.} \quad & \sum_{\delta^+(s)} x_a = 1 \\
 & - \sum_{\delta^-(s)} x_a = -1 \\
 & \sum_{\delta^+(s)} x_a - \sum_{\delta^-(s)} x_a = 0, \quad \forall i \neq s, t.
 \end{aligned}$$

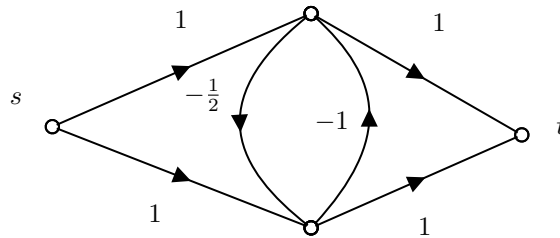
where

$$b_i = \begin{cases} 1, & i = s \\ -1, & i = t \\ 0, & \text{o.w.} \end{cases}.$$

However, this formulation has a problem, consider a cycle in the network with all arcs having cost  $-1$ , then the LP is unbounded by repeating on the cycle.



Even if we add  $x_a \leq 1$ , we can still have a walk but not necessarily a path.



Notice that for the network above, the shortest path has cost 1, but the LP can give a shortest path with cost  $1/2$  even if having constraints  $x_a \leq 1$ , which actually represents a walk that goes through the cycle once.

**Condition:** SP can be solved as a network flow problem if the network does not have directed cycles of net negative cost. e.g.: non-negative costs, no (directed) cycles.

*Remark.* In general, if there is a negative cost cycle, then the problem is NP-hard.

### Theorem 1.6: Principle of Optimality

Assume that there is cycle of net negative cost. If  $P$  is an  $s - t$  shortest path and  $i, j \in P$  ( $i$  precedes  $j$  in  $P$ ), then the  $i - j$  sub-path  $\hat{P}$  is an  $i - j$  shortest path.

*Proof.* Suppose there is an  $i - j$  path  $\tilde{P}$  for contradiction such that  $\sum_{a \in \tilde{P}} c_a < \sum_{a \in \hat{P}} c_a$ . Replace  $\hat{P}$  with  $\tilde{P}$  in  $P$  to obtain  $P'$ . If  $P'$  is a path, we are done. If it is a walk, then there exists cycle which we can delete can strictly decrease the cost. That is,  $P'$  is a cheaper path than  $P$ , contradiction.  $\square$

### Corollary 1.7

Let  $y_i^*$  be the shortest path cost from  $i$  to  $t$ . Then  $y_i^* \leq c_{ij} + y_j^*$ ,  $\forall (i, j) \in A$ .  
(Same thing in reverse:  $\hat{y}_i$  is a shortest path cost from  $s$  to  $i$ , then  $\hat{y}_j \leq c_{ij} + \hat{y}_i$ .)

Consider the dual of the LP:

$$\begin{aligned} \max \quad & y_s - y_t \\ \text{s.t.} \quad & y_i - y_j \leq c_{ij}, \quad \forall (i, j) \in A \end{aligned}$$

*Note.* if  $(y_i)$  is feasible, then  $(y_i + \alpha)$  is also feasible for any  $\alpha \in \mathbb{R}$  and has the same objective value. Thus, the linearity space is no empty. Thus, there is at least one constraint in the primal that is redundant, and we can then

assume the dual variable corresponding to the redundant primal constraint to be 0. If we sum all the primal constraint up, we can see that the constraint corresponding to  $t$  is redundant and thus WLOG, assume  $y_t = 0$ . Then we have,

$$\begin{aligned} \max y_s \\ \text{s.t. } y_i \leq c_{ij} + y_j, \forall (i, j) \in A, \end{aligned}$$

which is we have from the principle of optimality corollary; opt  $y^*$  encodes distances to  $t$ . With complementarity,  $(i, j)$  can only be in a shortest path if  $y_i^* = c_{ij} + y_j^*$ .

Analogously, if we set  $y_s = 0$  instead, then  $-y$  encodes distances from  $s$ .

### Definition 1.8: Directed Acyclic Graph

A directed graph is called a directed acyclic graph if it does not contain a cycle.

### Definition 1.9: Topological Sort

A topological sort of a directed graph is a labeling of nodes such that  $i < j$  for every  $(i, j) \in A$ .

### Proposition 1.10

A network is a directed acyclic graph iff it has a topological sort.

*Proof.*

- ( $\Leftarrow$ ): If there is a cycle, then following the cycle,  $i < j_1 < \dots < j_k < i$ , contradiction.
- ( $\Rightarrow$ ):

*Claim.* If acyclic, there exists  $v \in N$  with  $\delta^-(v) = \emptyset$ .

*Proof of the Claim.* Perform a search starting from an arbitrary node backwards following the incoming arcs. By the finiteness of the network, we either get a cycle or a node without incoming arcs.  $\square$

---

**Input:**  $(N, A)$ ,  $i \leftarrow 1$ .

**while**  $N \neq \emptyset$  **do**

    choose any  $v \in N$  with  $\delta^-(v) = \emptyset$

    label( $v$ )  $\leftarrow i$ ;  $i++$

$N \leftarrow N \setminus v$ , update  $A$

**end while**

---

*Claim.* At assignment of label  $i$ ,  $(1, \dots, i)$  is a valid top. sort for the network induced by  $1, \dots, i$ .

*Proof of the Claim.*

- Base case:  $i = 1$ , trivial.
- Induction:  $i \geq 2$ ,  $(1, \dots, i-1)$  is top. sort, any arc with head  $i$  must have tail  $\leq i-1$ .

$\square$

$\square$



**Algorithm 1** Bellman-Ford

---

```

 $y_n \leftarrow 0$ 
for  $i = n - 1, n - 2, \dots, 1$  do
     $y_i \leftarrow \min_{(i,j) \in A} \{c_{ij} + y_j\}$ 
    [succ(i)  $\leftarrow j$ ]
end for

```

---

**1.3 Shortest Path on Direct Acyclic Networks**

Given  $c \in \mathbb{R}^A$ , we can assume  $\delta^-(s) = \delta^+(t) = \emptyset$ . Find topological sort with  $(s = 1, \dots, t = n)$ .

- Running Time:  $\mathcal{O}(m)$ , topological sort and assigning values to  $y_i$ .
- Correctness: induction (backwards) at step  $i$ , labels  $y_i, \dots, y_n$  are correct.

*Proof.* –  $i = n$ , trivial.

- $i < n$ , suppose  $y_i = c_{ij} + y_j = c_{ij} + \sum_{a \in P} c_a$  where  $P$  is a shortest  $j - t$  path. All  $i - t$  paths use same arc  $(i, k)$  implies that  $y_i \leq c_{ik} + y_k \leq \text{cost of any } i - t \text{ path that uses } (i, k)$ . That is, the cost of any  $i - t$  path uses  $(i, k)$  has cost more than  $y_i$ ; thus, when we have  $y_i$  equal to the cost of  $i - t$  path through  $(i, j)$  and shortest path from  $j$  to  $t$ , also, this value is the smallest among all  $c_{ik} + y_k$  thus less than or equal to the cost of all paths from  $i - t$  through  $(i, k)$ .

□

Notice that, the reason that we need a top. sort is that for  $(i, j) \in A$ ,  $i$  is the tail and  $j$  is the head, by the top. sort,  $j$  must be greater than  $i$ .

**BF on General Networks use "stages"** Paths have  $\leq n - 1$  arcs. Then, the induction claim becomes:

---

```

 $y_i^0 \leftarrow 0; y_i^0 \leftarrow \infty, \forall i \neq t$ 
for  $k = 1, \dots, n - 1$  do
    for  $i \in N \setminus t$  do
         $y_i^k := \min\{y_i^{k-1}, \min_{(i,j) \in A} \{c_{ij} + y_j^{k-1}\}\}$ 
    end for
end for

```

---

*Claim.*  $y_i^k$  is the  $i - t$  Shortest path cost when using  $\leq k$  arcs.

*Proof.* Similar to the proof of the previous induction claim.

□

The running time now becomes  $\mathcal{O}(mn)$  might be worse than Dijkstra when the costs are nonnegative.

**Theorem 1.11**

*If the network has a negative cost cycle, following the above algorithm,  $y_i^n < y_i^{n-1}$  for some  $i$ .*

*Proof.* Take a cycle  $C$ , and suppose that  $y_i^n = y_i^{n-1}$  for all  $i \in C$ . Then,

$$y_i^n \leq c_{ij} + y_j^{n-1} = c_{ij} + y_j^n \text{ for } (i, j) \in C.$$

Thus,

$$\sum_{(i,j) \in C} y_i^n - y_j^n \leq \sum_{(i,j) \in C} c_{ij} \implies 0 \leq \sum_{(i,j) \in C} c_{ij}.$$

□

### 1.3.1 (Deterministic) Dynamic Programming (finite state, action, horizon)

Another name for shortest path on directed acyclic network, Knapsack:

$$\begin{aligned} \max \quad & \sum_{i=1}^n c_i x_i \\ \text{s.t.} \quad & \sum_{i=1}^n a_i x_i \leq b \\ & a \in \mathbb{N}^n, b \in \mathbb{N}, x_i \in \{0, 1\}, \forall i = 1, \dots, n. \end{aligned}$$

Knapsack as DP [SP]; nodes [states]; arcs[actions]. Let the current candidate item be  $i = 1, \dots, n$ , and the remaining capacity  $s = 0, \dots, b$ . Then, consider the state  $(i, s)$  which has arcs from it to  $(i + 1, s)$  without any cost and to  $(i + 1, s - a_i)$  where  $s \geq a_i$  with cost  $-c_i$ . Thus, the number of nodes is  $\mathcal{O}(nb)$ , the number of arcs is  $\mathcal{O}(nb)$  and the start point is  $(1, b)$ . The BF complexity is  $\mathcal{O}(nb)$  which, in precise, is  $\mathcal{O}(n2^{\log_2 b})$

## 1.4 Max Flow

Given a network  $(N, A)$ ; source  $s$  and a sink  $t$  in  $N$ ; arc capacities  $v \in (\mathbb{R}_+ \cup \{\infty\})^A$ . Add a dummy arc from  $t$  to  $s$ . How much can flow from  $s$  to  $t$ ?

$$\begin{aligned} \min \quad & -x_{ts} \\ \text{s.t.} \quad & \sum_{\delta^+(s)} x_a + \sum_{\delta^-(t)} x_a = x_{ts} \\ & \sum_{\delta^+(i)} x_a - \sum_{\delta^-(i)} x_a = 0, \forall i \in N \setminus \{s, t\} \\ & 0 \leq x_a \leq u_a, \forall a \in \tilde{A} \\ & 0 = x_a, a \in \hat{A} \end{aligned}$$

#### Definition 1.12

$s$ - $t$  cut:  $F \subseteq A$  such that  $(N, A \setminus F)$  has no  $s$ - $t$  path; capacity of a cut  $F$ :  $u(F) = \sum_{a \in F} u_a$ ; minimal cuts:  $S \subseteq N \setminus t, S \ni s$ , where we let  $\delta_+(S)$  be the cut defined by  $S$ .

#### Theorem 1.13

*Weak Duality: for any feasible  $s$ - $t$  flow  $x$  and any cut  $S$ ,*

$$x_{ts} \leq u(S)$$

*Proof.*  $x_{ts} + \sum_{\delta^+(S)} x_a = \sum_{\delta^+(S)} x_a - \sum_{\delta^-(S)} x_a \leq \sum_{\delta^+(S)} u_a$ . □

#### Theorem 1.14: [Max-Flow Min-Cut]

$$\max_{s-t \text{ flows}} x_{ts} = \min_{s \in S \subseteq N \setminus t} u(S)$$

Dual of the LP:

$$\begin{aligned}
 \min_{a \in \tilde{A}} \quad & u_a z_a \\
 & y_t - y_s \geq 1 \\
 & y_i - y_j \geq 0, \forall (i, j) \in \hat{A} \\
 & y_i - y_j + z_{ij} \geq 0, \forall (i, j) \in \tilde{A} \\
 & z \geq 0.
 \end{aligned}$$

Reminder of the primal:

$$\begin{aligned}
 \max_{x \geq 0} \quad & x_{ts} \\
 & \sum_{\delta^+(i)} x_a - \sum_{\delta^-(i)} x_a = 0, \forall i \in N \\
 & x_a \leq u_a, \forall a \in \tilde{A}
 \end{aligned}$$

WLOG, set  $y_s = 0$ , then we can set  $y_t = 1$ . By totally unimodular, we can set  $y \in \mathbb{Z}^N$  and  $z_a \in \mathbb{Z}_{\geq 0}$ , and we need  $y \in \{0, 1\}^N$  which implies  $z_{ij} = 1$  when  $y_j = 1, y_i = 0$  and 0 otherwise). Then, the optimal  $y^* \in \{0, 1\}^n$  defines the cut.  $S = \{i : y_i^* = 0\}$ ,  $z_{ij}^* = 1$  correspond to arcs in  $\delta^+(S)$ .

- $y \geq 0$ : suppose  $y_i < 0$  for some  $i$ . Replace all such  $y_i$  by 0.
- $y \leq 1$ : set  $y_i \leftarrow 1$  if  $y_i > 1$ .
- Complementary Slackness:

$$\begin{aligned}
 x_{ij}(y_i - y_j) &= 0, (i, j) \in \hat{A} \\
 x_{ij}(y_i - y_j + z_{ij}) &= 0, (i, j) \in \tilde{A} \\
 z_{ij}(u_{ij} - x_{ij}) &= 0, (i, j) \in \tilde{A}.
 \end{aligned}$$

Thus, if  $y_i > y_j$ , then  $x_{ij} = 0$ , so for this arc  $(i, j)$ , there is no flow, which agrees with  $x_{ts} = \sum_{\delta^+(S)} x_a - \sum_{\delta^-(S)} x_a \leq \sum_{\delta^+(S)} u_a$  requires  $\sum_{\delta^-(S)} x_a$  for max flow being equal to the min cut. Similarly,  $x_{ij} = 0$  only when  $z_{ij} = 0$  and  $y_i > y_j$ , same to the above.  $z_{ij} > 0$  if and only if  $u_{ij} = x_{ij}$ , so there is only flow when the arc is used at capacity.

### 1.4.1 Max Flow Applications

#### Theorem 1.15: Hall's Theorem

Consider a bipartite network  $(N, E)$  where  $N = V \cup W$ ,  $V \cap W = \emptyset$ ,  $|V| = |W| = n$ . Necessary and sufficient condition for perfect matching (marriage condition): for  $X \subseteq V$ , need  $|\Gamma(X)| \geq |X|$ .

*Proof.* Let  $s$  having arcs from  $s$  to each vertex in  $V$ , and each vertex has arcs to  $t$ , each of them has capacity 1. For arcs between  $V, W$ , let their capacity be  $\infty$ .

Clearly,  $(N, E)$  has a perfect matching iff the max flow in the network built has value  $|V| = |W| = n$ . If the max flow has value  $< n$ , we want to show that some  $X \subseteq V$  violates the marriage condition. Suppose so, then the min cut has capacity  $< n$  (by the fact any max flow has to use all capacity on the arcs). Then this cut cannot have any arc between  $V, W$ , so the cut  $S$  has  $S \cap V \neq \emptyset$ , and if  $i \in S \cap V$ , then  $j \in \delta(i)$  also has  $j \in S$ . Capacity of  $S$  is  $|V \setminus S| + |W \setminus S| = n - |V \cap S| + |\delta(S \cap V)| < n$  since  $S$  is a min cut. Then  $|\Gamma(S \cap V)| < |S \cap V|$ , contradiction.  $\square$

## 2 Traveling Salesman Problem

### 2.1 TSP

Consider a depot: 0; customers:  $N = \{1, \dots, n\}$ ;  $c_{ij}$ : cost of direct travel from  $i$  to  $j$ . Goal: minimum cost Hamiltonian cycle "tour". Assume  $c \geq 0$  and a complete network; triangle inequality:  $c_{ij} \leq c_{ik} + c_{kj}$ . Maybe: symmetry:  $c_{ij} = c_{ji}$ .

**IP formulation:**

$$x_{ij} = \begin{cases} 1, & \text{if tour includes } (i, j); \\ 0, & \text{otherwise.} \end{cases}$$

$$\begin{aligned} \min \quad & \sum_{i,j \in N \cup \{0\}, i \neq j} c_{ij} x_{ij} \\ \text{s.t.} \quad & \sum_{\delta^+(i)} x_a = \sum_{\delta^-(i)} x_a = 1, \quad \forall i \in N \cup \{0\} \\ & \sum_{\delta^+(S)} x_a \geq 1, \quad \emptyset \neq S \subseteq N \\ & x_{ij} \in \{0, 1\}. \end{aligned}$$

where the second constraint is called the subtour elimination constraint, there would be exponentially many of such constraints. For undirected graphs, we have  $\sum_{\delta(i)} x_e = 2$  and  $\sum_{\delta(S)} x_e \geq 2$  instead.

**DP formulation (Held+Karp):** When building a tour, need current location and remaining customers to visit.

- State:  $(i, S)$ ,  $i \in N \cup \{0\}$ ,  $S \subseteq N$ .
- Action:  $j \in S$  if  $S \neq \emptyset$ , 0 if  $S = \emptyset$ .
- Number of states:  $\Theta(n2^n)$ .
- Number of actions:  $\Theta(n^2 2^n)$ .

**Lower Bounds and Relaxations** Forward Star: cheapest arc from every forward start

$$\begin{aligned} \min_{x \geq 0} \quad & \sum c_a x_a \\ & \sum_{\delta^+(i)} x_a = 1, \quad i \in N \cup \{0\}. \end{aligned}$$

**Assignment Bound**

$$\begin{aligned} \min_{x \geq 0} \quad & \sum c_a x_a \\ & \sum_{\delta^+(i)} x_a = 1 \\ & \sum_{\delta^-(i)} x_a = 1. \end{aligned}$$

**Min. Spanning Tree (for the undirected graph)** Hamiltonian cycle is a Hamiltonian path plus an edge. Hamiltonian path is a spanning tree. If  $c \geq 0$ , MST is a lower bound.

Take  $S \subseteq N$ ,

$$\begin{aligned} \sum_{i \in S} \sum_{\delta(i)} x_e &= 2|S| \\ &= 2 \sum_{e \subseteq S} x_e + \sum_{\delta(S)} x_e \end{aligned}$$

By subtracting  $\sum_{\delta(S)} x_e \geq 2$ , we get

$$\sum_{e \subseteq S} x_e \leq |S| - 1.$$

Then,  $\sum_{i \in N \cup \{0\}} \sum_{\delta(i)} x_e = 2(n+1) = 2 \sum_e x_e$ . Consider

$$\begin{aligned} \min_{x \geq 0} \quad & \sum_e c_e x_e \\ & \sum_e x_e = n+1 \\ & \sum_{e \subseteq S} x_e \leq |S| - 1, S \subsetneq N \cup \{0\} \end{aligned}$$

Notice that when we change  $n+1$  to  $n$ , the corresponding coefficient in the objective function of the dual decrease. Since the inequalities are  $\leq$ , the corresponding variables in the dual are  $\leq 0$ , the only possible nonnegative variable is the one corresponding to the equality. However, since the objective function of the primal is nonnegative (when  $c \geq 0$ ), the dual variable corresponding to the equality has to be nonnegative, changing  $n+1$  to  $n$  decreases the objective value of the dual, thus it's a lower bound.

**0-tree** a TSP tour is a Hamiltonian cycle through  $N$  plus two edges connecting  $N$  to  $O$  (so you create a unique cycle including 0). Can be optimized with greedy algorithm (like minimum spanning tree problem).

$$\begin{aligned} \min \quad & \sum_e c_e x_e \\ & \sum_{\delta(0)} x_e = 2 \\ & \sum_{e \subseteq N} x_e = n-1 \\ & \sum_{e \subseteq S} x_e \leq |S| - 1, \forall S \subseteq N \\ & 0 \leq x_e \leq 1. \end{aligned}$$

**0-Tree Bound + Lagrangian Relaxation for Symmetric TSP**  $\pi(2 - \sum_{\delta(i)} x_e) = 0$  for any TSP tour, set  $\pi_0 = 0$ . Then we can consider the objective function

$$\sum_{i,j} c_{ij} x_{ij} + \sum_{i \in N \cup \{0\}} \pi_i (2 - \sum_{\delta(i)} x_i) = \sum_{i,j} (c_{ij} - \pi_i - \pi_j) x_{ij} + 2 \sum_i \pi_i,$$

which implies that for any  $\pi \in \mathbb{R}^N$ , the cost of optimal 0-tree w.r.t. this objective plus  $2 \sum_i \pi_i$  gives a lower bound.

$$f(\pi) = 2 \sum_i \pi_i + \min_{0\text{-tree } T} \left\{ \sum_{ij \in T} (c_{ij} - \pi_i - \pi_j) \right\},$$

want  $\max_{\pi \in \mathbb{R}^N} f(\pi)$ . Notice that  $f$  is concave and piece-wise linear in  $\pi$  because  $\sum_{ij \in T} (c_{ij} - \pi_i - \pi_j)$  is linear in  $\pi$ .

Optimize 0-tree:  $\deg(i) = 1$ , then increase  $\pi_i$ ;  $\deg(i) > 2$ , then decrease  $\pi_i$ .

$$\begin{aligned} \max_{\pi \in \mathbb{R}^N} & 2 \sum_{i \in N} \pi_i + \min_{x \geq 0} \sum_{i,j} (c_{ij} - \pi_i - \pi_j) x_{ij} \\ \text{s.t.} & \sum_{\delta(0)} x_e = 2 \\ & \sum_{e \subseteq N} x_e = n - 1 \\ & \sum_{e \subseteq S} x_e \leq |S| - 1, \forall \emptyset \neq S \subseteq N \\ & [x_e \in \{0, 1\}] \end{aligned}$$

where the constraint  $\delta_{\delta(i)} x_e = 2$  is dropped and we penalize it in the objective function. IP theory implies that, since the polyhedron defining this relaxation is integral, the value of the Lagrangian relaxation equals the LP relaxation.

$$\begin{aligned} \min & \sum_{i,j \in N \cup \{0\}, i \neq j} c_{ij} x_{ij} \\ \text{s.t.} & \sum_{\delta^+(i)} x_a = \sum_{\delta^-(i)} x_a = 1, \forall i \in N \cup \{0\} \\ & \sum_{\delta^+(S)} x_a \geq 1, \emptyset \neq S \subseteq N \quad (\star) \end{aligned}$$

Let  $\mathcal{S} \subseteq 2^N$ .

---

**while do:**

Solve LP with  $(\star)$  for  $S \in \mathcal{S}$ , get solution  $\hat{x}$ .

check:  $\min_{\emptyset \neq S \subseteq N} \left\{ \sum_{\delta^+(S)} \hat{x}_a \right\} < 1$  (global) MINCUT

**if**  $\geq 1$  **then**

Done, exist

**else**

add minimizing  $S$  to  $\mathcal{S}$

**end if**

**end while**

---

## 2.2 Approximate LP

**Relaxation technique for DP** TSP: state  $(i, S)$

$$\begin{aligned} \max & y_{0,N} \\ \text{s.t.} & y_{i,S} \leq c_{ij} + y_{i,S \setminus j}, \forall i \in N, S \subseteq N \setminus i, S \neq \emptyset, \\ & y_{i,\emptyset} \leq c_{i0}, \forall i \in N, \end{aligned}$$

any feasible  $y$  gives a lower bound.

A primal relaxation is equivalent to a dual restriction.

$$y_{i,S} \approx \lambda \cdot b_{i,S}$$

where  $b_{i,S}$  is a basis vector and  $\lambda$  are weights. e.g.  $y_{i,S} \approx \lambda |S| + \sum_{k \in N \cup 0} \lambda_k \mathbb{1}(i = k)$ .

*Example 2.1.*  $y_{i,S} = \sum_{k \in S \cup i} \lambda_k + \sum_{k \in S \cup 0} \mu_k$ ,  $\lambda, \mu \in \mathbb{R}^{N \cup 0}$ . Interpret  $\lambda$  as the cost of leaving the node and  $\mu$  as the cost of entering the node.

$$y_{i,S} - y_{j,S \setminus j} = \lambda_i + \mu_j.$$

$$\begin{aligned} \max y_{0,N} &= \sum_{k \in N \cup 0} (\lambda_k + \mu_k) \\ \text{s.t. } \lambda_i + \mu_j &\leq c_{ij}, \quad i, j \in N \cup 0. \end{aligned}$$

And the dual is

$$\begin{aligned} \min \sum_{i,j} c_{ij} x_{ij} \\ \text{s.t. } \sum_{\delta^+(i)} x_a + \sum_{\delta^-(i)} x_a &= 1, \quad \forall i \end{aligned}$$

## 2.3 TSP Heuristic

We consider the worst-case analysis of a minimization problem.

### Definition 2.1

Let  $C_H(I)$  be the cost of a heuristic  $H$  for an instance  $I$ , and  $C^*(I)$  be the optimal cost of  $I$ . If  $C_H(I) \leq \alpha C^*(I)$  for all  $I$ , then we say  $H$  is an  $\alpha$ -approximation algorithm where  $\alpha \in [1, \infty)$ .

### 2.3.1 Minimum Spanning Tree(MST) Heuristic for Symmetric TSP

Assume triangle inequality is satisfied.

#### Algorithm 2 MST

**Step 1:** Construct MST on  $N \cup \{0\}$ . Call it  $T$ .

**Step 2:** Replace each edge with two arcs in  $T$  with the same weight. The created graph has vertices with all degrees even. That is, if  $\{u, v\} \in T$ , delete it and add arcs  $(u, v), (v, u)$ .

**Step 3:** Construct Eulerian tour through  $T$ , which is guaranteed to exist by the even degree property.

**Step 4:** Every time the tour repeats a node, "short cut" to the next node. That is, in the tour, delete the repeated node and keep going, this only improves the tour by triangle inequality. Output this Hamiltonian cycle.

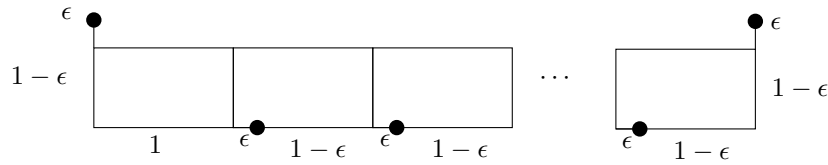
### Theorem 2.2

$$C_{Alg2}(I) \leq 2C^*(I)$$

for all symmetric instances with triangle inequality.

*Proof.*  $C_{MST} \leq C_{TSP}$  by the fact that any TSP can become a MST by deleting an edge.  $C_{Alg2} \leq 2C_{MST}$  by changing the edges to arcs and triangle inequality.  $\square$

*Example 2.2* (Tightness of the above Theorem (Johnson and Papadimitriou 1985)). Consider a graph of  $(1 - \epsilon) \times 1$  rectangles repeating  $n$  times and connect by the  $(1 - \epsilon)$  edge one by one. The set of vertices are  $\{(0, 0), (1, 0), (1 + \epsilon, 0), (2, 0), \dots, (n - 1 + \epsilon, 0), (n, 0), (0, 1 - \epsilon), (1, 1 - \epsilon), \dots, (n, 1 - \epsilon), (0, 1), (n, 1)\}$ . Use the Manhattan distance for triangles. Then MST has cost  $n(2 - \epsilon) + (1 - \epsilon) + 2\epsilon$ , MST heuristic has  $n(3 - 2\epsilon) + 2\epsilon + (2\epsilon + n)$ , OPT has  $2n + 2 + 4\epsilon$ . The ratio of  $C_{Alg2}/C_{OPT} = 2$  as  $n \rightarrow \infty$ .



### 2.3.2 Greedy Heuristics

---

**Algorithm 3** Nearest neighbor
 

---

```

 $i \leftarrow 0, S \leftarrow N, T \leftarrow \emptyset.$ 
while  $S \neq \emptyset$  do
   $j \leftarrow \arg \min_{k \in S} c_{ik}$ 
   $T \leftarrow T \cup \{ij\}, S \leftarrow S \setminus j$ 
   $i \leftarrow j$ 
end while
 $T \leftarrow T \cup \{i0\}$ 

```

---

To make it better: *insertion*.

---

**Algorithm 4** cheapest insertion
 

---

```

 $j \leftarrow \arg \min_{k \in N} \{c_{ek}\}$ 
 $T \leftarrow \{\{0, j\}, \{j, 0\}\}, S \leftarrow N \setminus j$ 
while  $S \neq \emptyset$  do
  choose  $j \in S$  insert into  $T$  as cheaply as possible:  $\min c_{ij} + c_{jk} - c_{ik}, \forall \{i, k\} \in T$ 
   $T \leftarrow T \cup \{\{i, j\}, \{i, k\}\} \setminus \{i, k\}$ 
   $S \leftarrow S \setminus j.$ 
end while

```

---

**Theorem 2.3**

$CI(I) \leq 2 \text{OPT}(I)$  for symmetric  $I$  with  $c \geq 0$ , triangle inequality. The ratio is tight.

*Proof.* Let  $\Xi$  be a minimum spanning tree. We inductively maintain it as a forest, s.t. each component contains one node of  $T$  (the tour) and vice versa. Initially,  $0 \in \Xi$  and  $\Xi$  is a tree. Induction: we insert  $j$ , some component  $\Xi_j$  contains  $j$  and also  $\ell \in T$ . In the unique  $j - \ell$  path in  $\Xi_j$ , delete edges  $\hat{e}$  incident to  $\ell$ . Insertion cost  $c_{ij} + c_{jk} - c_{ik} \leq 2\hat{c}_e$ .  $\square$