

Notes for Operations Research & More

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October 14, 2019

October 14, 2019

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Part I

Graph and Network Theory

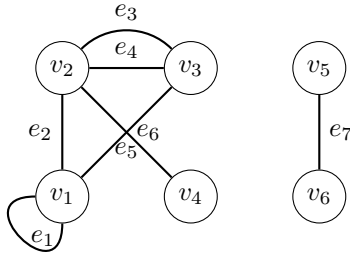
Chapter 1

Basic concepts

1.1 Graph

Definition 1.1.1 (Graph). A **graph** G consists of a finite set $V(G)$ on vertices, a finite set $E(G)$ on edges and an **incident relation** than associates with any edge $e \in E(G)$ an unordered pair of vertices not necessarily distinct called **ends**.

For example, the following graph



can be represented as

$$V = V(G) = \{v_1, v_2, v_3, v_4, v_5, v_6\} \quad (1.1)$$

$$E = E(G) = \{e_1, e_2, e_3, e_4, e_5, e_6, e_7\} \quad (1.2)$$

$$e_1 = v_1v_2, e_2 = v_2v_4, \dots \quad (1.3)$$

Definition 1.1.2 (loop, parallel, simple graph). An edge with identical ends is called a **loop**. Two edges having the same ends are said to be **parallel**. A graph without loops or parallel edges is called **simple graph**.

Definition 1.1.3 (adjacent). Two edges of a graph are **adjacent** if they have a common end, two vertices are **adjacent** if they are jointed by an edge.

1.2 Subgraph

Definition 1.2.1 (subgraph). Given two graphs G and H , H is a **subgraph** of G if $V(H) \subseteq V(G)$, $E(H) \subseteq E(G)$ and an edge has the same ends in H as it does in G . Furthermore, if $E(H) \neq E(G)$ then H is a proper subgraph.

Definition 1.2.2 (spanning). A subgraph H on G is **spanning** if $V(H) = V(G)$.

Definition 1.2.3 (vertex-induced, edge-induced). For a subset $V' \subseteq V(G)$ we define an **vertex-induced** subgraph $G[V']$ to be the subgraph with vertices V' and those edges of G having both ends in V' . The **edge-induced** subgraph $G[E']$ has edges E' and those vertices of G that are ends to edges in E' .

Notice: If we combine node-induced or edge-induced subgraphs $G(V')$ and $G(V - V')$, we cannot always get the entire graph.

Definition 1.2.4 (degree). Let $v \in V(G)$, then the **degree** of $v \in V(G)$ denote by $d_G(v)$ is defines to be the number of edges incident of v . Loops counted twice.

Theorem 1.1. For any graph $G = (V, E)$

$$\sum_{v \in V} d(v) = 2|E| \quad (1.4)$$

Proof. \forall edge $e = \mu v$ with $\mu \neq v$, e is and counted once for μ and once for v , a total of two altogether. If $e = \mu\mu$, a loop, then it is counted twice for μ . \square

Problem 1.1. Explain clearly, what is the largest possible number of vertices in a graph with 19 edges and all vertices of degree at least 3. Explain why this is the maximum value.

Solution. The maximum number is 12.

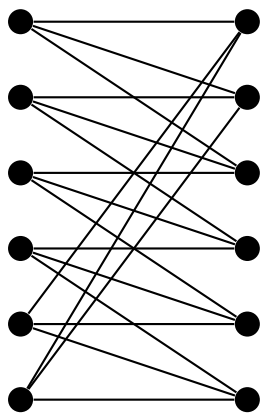
Proof. First we prove 12 vertices is possible, then we prove 13 vertices is not possible

- The following graph contains 12 vertices and 18 edges, each vertex has a degree of 3.

- For 13 vertices and each vertex has a degree of at least 3 will require at least

$$2|E| = \sum_{v \in V} d(v) \geq 3 \times |N| = 3 \times 13 \Rightarrow |E| \geq 19.5 > 19 \quad (1.5)$$

edges, i.e., 13 vertices is not possible.



□

Corollary 1.1.1. *Every graph has an even number of odd degree vertices.*

Proof.

$$V = V_E \cup V_O \Rightarrow \sum_{v \in V} d(v) = \sum_{v \in V_E} d(v) + \sum_{v \in V_O} d(v) = 2|E|$$

(1.6)

□

Chapter 2

Paths, Trees, and Cycles

2.1 Walk

Definition 2.1.1 (walk). A **walk** in a graph G is a finite sequence $w = v_0e_1v_1e_2...e_kv_k$, where for each $e_i = v_{i-1}v_i$ the edge and its ends exists in G . We say that walk w_0 to v_k on (v_0, v_k) -walk.

Example.

$$w = v_2e_4v_3e_4v_2e_5v_3 \quad (2.1)$$

is a walk, or (v_2, v_3) -walk

Definition 2.1.2 (origin, terminal, internal, length). For (v_0, v_k) -walk, The vertices v_0 and v_k are called the **origin** and the **terminal** of the walk w , $v_1..v_{k-1}$ are called **internal** vertices. The integer k is the **length** of the walk. Length of w equals to the number of edges.

We can create a reverse walk w^{-1} by reversing w .

$$w^{-1} = v_ke_kv_{k-1}e_{k-1}...e_2v_1 \quad (2.2)$$

(The reverse walk is guaranteed to exist because it is an undirected graph)

Given two walks w and w' we can create a third walk denoted by ww' by concating w and w' . The new walk's origin is the same as terminal.

2.2 Path and Cycle

Definition 2.2.1 (trail). A **trail** is a walk with no repeating edges. e.g., $v_3e_4v_2e_5v_3$

Definition 2.2.2 (path). A **path** is a trail with no repeating vertices. e.g., $v_3e_4v_2$

Notice: Paths \subseteq Trails \subseteq Walks

Definition 2.2.3 (closed, cycle). A path is **closed** if it has positive length and its origin and terminal are the same. e.g., $v_1e_2v_2e_4v_3e_3v_1$. A closed trail where origin and internal vertices are distinct is called a **cycle** (The only time a vertex is repeated is the origin and terminal)

Definition 2.2.4 (even/odd cycle). A cycle is **even** if it has a even number of edges otherwise it is **odd**.

Problem 2.1. Prove that if C_1 and C_2 are cycles of a graph, then there exists cycles $K_1, K_2, ..., K_m$ such that $E(C_1)\Delta E(C_2) = E(K_1) \cup E(K_2) \cup ... \cup E(K_m)$ and $E(K_i) \cap E(K_j) = \emptyset, \forall i \neq j$. (For set X and Y , $X\Delta Y = (X - Y) \cup (Y - X)$, and is called the symmetric difference of X and Y)

Proof. Proof by constructing $K_1, K_2, ...K_m$. Denote

$$C_1 = v_{11}e_{11}v_{12}e_{12}v_{13}e_{13}...v_{1n}e_{1n}v_{11} \quad (2.3)$$

$$C_2 = v_{21}e_{21}v_{22}e_{22}v_{23}e_{23}...v_{2k}e_{2k}v_{21} \quad (2.4)$$

Assume both cycle start at the same vertice, $v_{11} = v_{12}$. (If there is no intersected vertex for C_1 and C_2 , just simply set $K_1 = C_1$ and $K_2 = C_2$)

The following algorithm can give us all $K_j, j = 1, 2, ..., m$ by constructing $E(C_1)\Delta E(C_2)$. Also, the complexity is $O(mn)$, which makes the proof doable.

Algorithm 1 Find $K_1, K_2, ...K_m$ by constructing $E(C_1)\Delta E(C_2)$

Require: Graph G , cycle C_1 and C_2

Ensure: $K_1, K_2, ...K_m$

```

1: Initial,  $K \leftarrow \emptyset, j = 1$ 
2: Set temporary storage units,  $v_o \leftarrow v_{11}, v_t \leftarrow \emptyset$ 
3: for  $i = 1, 2, ..., n$  do
4:   if  $e_{1i} \in C_2$  then
5:     if  $v_o \neq v_{1i}$  then
6:        $v_t \leftarrow v_{1i}$ 
7:       concat  $(v_o, v_t)$ -path  $\subset C_1$  and  $(v_o, v_t)$ -path
          $\subset C_2$  to create a new  $K_j$ 
8:       Append  $K$  with  $K_j, K \leftarrow K \cup K_j$ 
9:       Reset temporary storage unit.  $v_o \leftarrow v_{1(i+1)}$ 
         (or  $v_{11}$  if  $i = n$ ),  $v_t \leftarrow \emptyset$ 
10:    else
11:       $v_o \leftarrow v_{1(i+1)}$  (or  $v_{11}$  if  $i = n$ )
12:    end if
13:  end if
14: end for
```

Now we prove that $K_i \cap K_j = \emptyset, \forall i \neq j$. For each K_j , it is defined by two (v_o, v_t) -paths in the algorithm. From the algorithm we know that all the edges in (v_o, v_t) -path

in C_1 are not intersecting with C_2 , because if the edge in C_1 is intersected with C_2 , either we closed the cycle K_j before the edge, or we updated v_o after the edge (start a new K_j after that edge). By definition of cycle, all the (v_o, v_t) -path that are subset of C_1 are not intersecting with each other, as well as all the (v_o, v_t) -path that are subset of C_2 . Therefore, $K_i \cap K_j = \emptyset, \forall i \neq j$. \square

Definition 2.2.5 (connected vertices). Two vertices u and v in a graph are said to be **connected** if there is a path between u and v .

Definition 2.2.6 (component). Connectivity between vertices is an equivalence relation on $V(G)$, if V_1, \dots, V_k are the corresponding equivalent classes then $G[V_1] \dots G[V_k]$ are **components** of G . If graph has only one component, then we say the graph is connected. A graph is connected iff every pair of vertices in G are connected, i.e., there exists a path between every pair of vertices.

Problem 2.2. If G is a simple graph with at least two vertices, prove that G has two vertices with the same degree.

Proof. A simple graph can only be connected or not connected.

- If G is connected, i.e., for all vertices, the degree is greater than 0. Also the graph is simple, for a graph with $|N|$ vertices, the degree of each vertex is less or equal to $|N| - 1$ (cannot have loop or parallel edge). For $|N|$ vertices, to make sure there is no two vertices that has same degree, it will need $|N|$ options for degrees, however, we only have $|N| - 1$ option. According to pigeon in holes principle, there has to be at least two vertices with the same degree.
- If G is not connected, i.e., the graph has more than one component. One of the following situation will happen:
 - For all components, each component contains only one vertex. Since we have at least two vertices, which means there are at least two component that has only one vertex. For those vertices, at least two vertices has the same degree as 0.
 - At least one component has more than one vertices. In this situation, we can find a component that has more than one vertices as a subgraph G' of the graph G . That G' is a connected simple graph by definition. We have already proved that a connected simple graph has two vertices with the same degree, which means G has two vertices with the same degree.

2.3 Tree and forest

Definition 2.3.1 (acyclic graph). A graph is called **acyclic** if it has no cycles

Definition 2.3.2 (forest, tree). A acyclic graph is called a **forest**. A connected forest is called a **tree**.

Theorem 2.1. Prove that T is a tree, if T has exactly one more vertex than it has edges.

Proof. 1. First we prove for any tree T that has at least two vertices, there has to be at least one leaf, i.e., now we prove that we can find u with degree of 1. Proof by constructing algorithm. (In fact we can prove that there are at least two leaves.)

Algorithm 2 Find one leaf in a tree

Require: $d(u) = 1$

Ensure: A tree T has at least one vertex

```

1: Let  $u$  and  $v$  be any distinct vertex in a tree  $T$ 
2: Let  $p$  be the path between  $u$  and  $v$ 
3: while  $d(u) \neq 1$  do
4:   if  $d(u) > 1$  then
5:     Let  $n(u)$  be the set of neighboring vertices of  $u$ 
6:     In  $n(u)$ , find a  $u'$  that the edge between  $u$  and
        $u'$ , denoted by  $e$ ,  $e \notin p$ 
7:      $u \leftarrow u'$ 
8:      $p \leftarrow p \cup e$ 
9:   end if
10: end while
```

The above algorithm is guaranteed to have an end because a tree is acyclic by definition

2. Then, if we remove one leaf in the tree, i.e., we remove an edge and a vertex, where that vertex only connects to the edge we removed. One of the following situations will happen:
 - (a) Situation 1: The remaining of T is one vertex. In this case, T has two vertices and one edge. (Exactly one more vertex than it has edges)
 - (b) Situation 2: The remaining of T is another tree T' (removal of edges will not change acyclic and connectivity), where $|V(T)| = |V(T')| + 1$ and $|E(T)| = |E(T')| + 1$. (one edge and one vertex has been removed)
3. Do the leaf removal process recursively to T' if Situation 2 happens until Situation 1 happens.

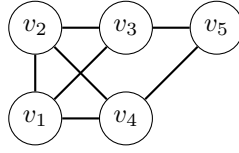
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2.4 Spanning tree

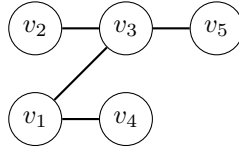
Definition 2.4.1 (spanning tree). A subgraph T of G is a **spanning tree** if it is spanning ($V(T) = V(G)$) and it is a tree.

\square

Example. In the following graph



This is a spanning tree



Problem 2.3. Prove that if T_1 and T_2 are spanning trees of G and $e \in E(T_1)$, then there exists a $f \in E(T_2)$, such that $T_1 - e + f$ and $T_2 + e - f$ are both spanning trees of G .

Proof. One of the following situation has to happen:

1. If for given $e \in E(T_1)$, $\exists f = e \in E(T_2)$, then $T_1 - e + f = T_1$, $T_2 + e - f = T_2$ are both spanning trees of G
2. If for given $e \in E(T_1)$, $e \notin E(T_2)$, the following will find an edge f that $T_1 - e + f$ and $T_2 + e - f$ are both spanning trees of G .
 - (a) T_1 is a spanning tree, removal of $e \in E(T_1)$ will disconnect the spanning tree into two components (by definition of spanning tree), denoted by $G_1 \subset G$ and $G_2 \subset G$, by definition, $V(G_1)$ and $V(G_2)$ is a partition of $V(G)$.
 - (b) Add e into T_2 . We can proof that by adding an edge into a tree will create exactly one cycle, denoted by C , $e \in E(C)$.
 - (c) For C , since it is a cycle and one end of e is in $V(G_1)$, the other end of e is in $V(G_2)$, there has to be at least two edges (can be more) that has one end in $V(G_1)$ and the other end in $V(G_2)$, denote the set of those edges as $E \subset E(C)$, one of those edges is $e \in E$
 - (d) Choose any $f \in E$ and $f \neq e$, for that f , $T_1 - e + f$ and $T_2 + e - f$ are both spanning trees of G .
 - (e) Prove that $T_1 - e + f$ is a spanning tree
 - i. $T_1 - e + f$ have the same set of vertices as T_1 , therefore it is spanning.
 - ii. It is connected both within G_1 and G_2 , for f , one end is in $V(G_1)$, the other end is in $V(G_2)$ therefore $T_1 - e + f$ is connected.

- iii. $T_1 - e + f$ have the same number of edges as T_1 , which is $|T_1| - 1$, therefore $T_1 - e + f$ is a tree. (We have proven the connectivity in the previous step.)
- iv. $T_1 - e + f$ is spanning, connected, a tree, therefore it is a spanning tree.

(f) Prove that $T_2 + e - f$ is a spanning tree

- i. $T_2 + e - f$ have the same set of vertices as T_2 , therefore it is spanning.
- ii. T_2 is connected, adding an edge will not break connectivity, therefore $T_2 + e$ is connected, removing an edge in a cycle will not break connectivity, therefore $T_2 + e - f$ is connected.
- iii. $T_2 - e + f$ have the same number of edges as T_2 , which is $|T_2| - 1$, therefore $T_2 + e - f$ is a tree. (We have proven the connectivity in the previous step.)
- iv. $T_2 - e + f$ is spanning, connected, a tree, therefore it is a spanning tree.

□

Theorem 2.2. Every connected graph has a spanning tree.

Proof. Prove by constructing algorithm: □

Algorithm 3 Find a spanning tree for connected graph (Prim's Algorithm in unweighted graph)

Require: a connected graph G and an enumeration e_1, \dots, e_m of the edges of G

Ensure: a spanning tree T of G

- 1: Let T be the spanning subgraph of G with $V(T) = V(G)$ and $E(T) = \emptyset$
- 2: $i \leftarrow 1$
- 3: **while** $i \leq |E|$ **do**
- 4: **if** $T + e_i$ is acyclic **then**
- 5: $T \leftarrow T + e_i$
- 6: $i \leftarrow i + 1$
- 7: **end if**
- 8: **end while**

Notice: This algorithm can be improved, one idea is to make summation of edges in spanning subgraph less or equation to $|V| - 1$

For the complexity of spanning tree algorithm:

1. Space complexity, $2|E|$, which is $O(|E|)$
2. Time complexity
 - (a) How to check for acyclic?
 - i. At every stage T has certain components V_1, \dots, V_t , (every time we add an edge, the number of components minus 1)

- ii. So at the beginning $t = |V|$ with $|V_i| = 1 \forall i$ and at the end, $t = 1$.
- (b) Count the amount of work for the algorithm.
 - i. Need to check for acyclic for each edge, which costs $O(|E|)$
 - ii. Need to flip the pointer for each vertex, for each vertex, at most will be flipped $\log |V|$ times, altogether $|V| \log |V|$ times.
 - iii. The time complexity is $O(|E| + |V| \log |V|)$
3. First we need to input the data, create an array such that the first and the second entries are the ends of e_1 , third and fourth are the ends of e_2 , and so on.
4. The amount of storage needs in $2|E|$, which is $O(|E|)$
5. The main work involved in the algorithm is for each edges e_i and the current T , to determine if $T + e_i$ creates a cycle.
6. suppose we keep each component V_i by keeping for each vertex a pointer from the vertex to the name of the component containing it. Thus if $\mu \in V_3$, there will be a pointer from μ to integer 3.
7. Then when edge $e_i = \mu v$ is encountered in Step 2, we see that $T + e_i$ contains a cycle if and only if μ and v point to same integer which means they are in the same component
8. If they are not in the same component, we want to add the edge which means then I have to update the pointers.

To prove algorithm we need to show the output is a spanning tree, which means three properties must hold:

- spanning (Step I)
- acyclic (We never add an edge that create a cycle)
- connected (Proof by contradiction)

So it is sufficient to show that the output will be connected.

Proof. (Proof by Contradiction) Suppose the output graph T of the algorithm is NOT connected. Let T_1 be a component of T , let $x \in T_1$ and $y \notin T_1$. But G is a connected graph (given from the beginning), so there must be a path in G that connects x and y . Let such a path in G be $p = xe_1v_1e_2..v_{k-1}e_kv_ky$. Clearly, $p \notin T_1$. So there must be a first vertex in P that not in T_1 . So $e_i \notin E(T)$, the only way this can happen when applying the algorithm is if $T + e_i$ creates a cycle C , i.e., $e_i \in C$, so $C - e_i$ is a path connecting v_{i-1} and v_i . So $C - e_i \in T$, so v_{i-1} is connected to $v_i \in T$. Contradiction. \square

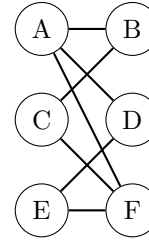
2.5 Special Graphs

Definition 2.5.1. A **complete** graph $K_n (n \geq 1)$ is a simple graph with n vertices and with exactly one edge between each pair of distinct vertices.

Definition 2.5.2. A **cycle** graph $C_n (n \geq 3)$ consists of n vertices v_1, \dots, v_n and n edges $\{v_1, v_2\}, \{v_2, v_3\}, \dots, \{v_{n-1}, v_n\}$

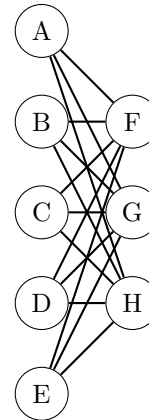
Definition 2.5.3. A **wheel** graph $W_n (n \geq 3)$ is a simple graph obtains by adding one vertex to the cycle graph C_n , and connecting this new vertex to all vertices of C_n

Definition 2.5.4. A simple graph is said to be **bipartite** if the vertex set can be expressed as the union of two disjoint non-empty subsets V_1 and V_2 such that every edges has one end in V_1 and another end in V_2



Definition 2.5.5 (complete bipartite). The **complete bipartite** graph K_{mn} is the bipartite graph V_1 containing m vertices and V_2 containing n vertices such that each vertex in V_1 is adjacent to every vertex in V_2

Example. Here is an example for K_{53}



Theorem 2.3. (König) A graph G is bipartite iff every cycle is even.

Proof. Hereby we prove the \Rightarrow and \Leftarrow

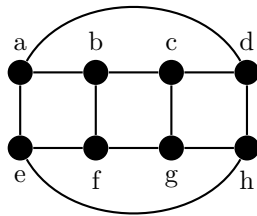
- (\Rightarrow) If the graph G is bipartite, by definition, the vertices of graph can be partition into two groups, that within the group there is no connection between vertices. Therefore, for each cycle, the odd index of

vertices and even index of vertices has to be choose alternatively from each groups. Therefore the cycle has to be even.

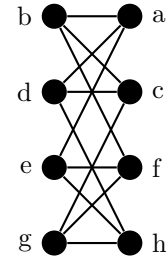
- (\Leftarrow) Prove by contradiction. A graph can be connected or not connected.
 - If G is connected and has at least two vertices, for an arbitrary vertex $v \in V(G)$, we can calculate the minimum number of edges between the other vertices v' and v (i.e., length, denoted by $l(v', v)$), for all the vertices that has odd length to v , assign them to set V_1 , for the rest of vertices (and v), assign to set V_2 . Assume that G is not bipartite, which means there are at least one edge between distinct vertices in set V_1 or set V_2 , without lost of generality, assume that edge is uw , $u, w \in V_1$. For all vertices in V_1 there is an odd length of path between the vertex and v , therefore, there exists an odd $l(u, v)$, and an odd $l(w, v)$. The length of cycle $l(u, w, v) = 1 + l(u, v) + l(w, v)$, which is an odd number, it contradict with the prerequisite that all cycles are even, which means the assumption that G is not bipartite is incorrect, G should be bipartite.
 - If G is not connected. Then G can be partition into a set of disjoint subgraphs which are connected with at least two vertices or contains only one vertex. For the subgraph that has more that one vertices, we already proved that it has to be bipartite. For the subgraph $G_i \subset G, i = 1, 2, \dots, n$, the vertices can be partition into $V_{i1} \in V(G_i)$ and $V_{i2} \in V(G_i)$, where $V_{i1} \cap V_{i2} = \emptyset$, the union of those subgraphs are bipartite too because $V_1 = \cup_{i=1}^n V_{i1} \in V(G)$ and $V_2 = \cup_{i=1}^n V_{i2} \in V(G)$ satisfied the condition of bipartite. For the subgraph that has one one vertices, those vertices can be assigned into either V_1 or V_2 .

□

Example. The following graph is bipartite, it only contains even cycles.

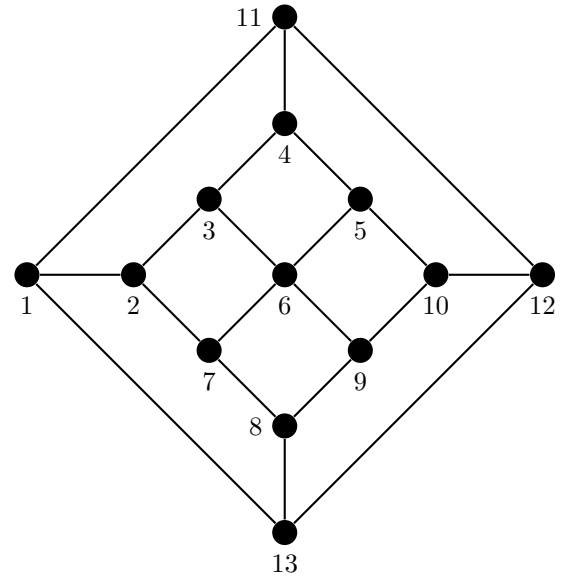


We can rearrange the graph to be more clear as following



The vertices of graph G can be partition into two sets, $\{a, c, f, h\}$ and $\{b, d, e, g\}$

Example. The following graph is not bipartite



The cycle $c = v_1v_1v_4v_3v_2$ have odd number of vertices.

Chapter 3

Complexity

3.1 Complexity

FIXME This part is going to be moved to Algorithm notes (or I will just delete this part because of duplication). We want to know guaranteed performances - "worse case" scenarios - for any algorithm working on any problem instance.

The following example is for addition of two matrices:

Algorithm 4 Add two $m \times n$ matrices A, B to get matrix C

```
for  $i = 1, 2, \dots, m$  do
  for  $j = 1, 2, \dots, n$  do
     $C_{ij} = A_{ij} + B_{ij}$ 
  end for
end for
```

The "running time" of an algorithm is measured by the number of basic operational steps.

For so called "basic" steps, it includes

- $+, -, \times, \div$
- assignments and storage of a variable
- comparisons

For the example above

- $c_1 mn$ for addition $C_{ij} = A_{ij} + B_{ij}$
- $c_2 mn$ for saving C_{ij}
- $c_3 mn$ for comparison and assignment for i and j

c_1, c_2, c_3 does not matter, the number of steps are $m \times n$, we say the algorithm runs $O(mn)$ (big O notation, the worse case)

Example. $f(n) = 3n^3 + 4n^2$

Claim: $f(n)$ is $O(n^3)$

Proof: Find a c for $cn^3 - 3n^3 - 4n^2$ that there exist a n_0 , for $\forall n \geq n_0$, the inequality holds.

3.2 O notation, Omega notation, Theta notation

Definition 3.2.1 (O notation). An algorithm is said to run in $O(f(n))$ time if for some constant $C(\geq 0)$, and n_0 the time takes algorithm is at most $Cf(n)$ for all $n \geq n_0$

Definition 3.2.2 (Ω notation). An algorithm is said to run in $\Omega(f(n))$ time if for some constant $C'(\geq 0)$, and n_0 . For all instance $n \geq n_0$, the time takes algorithm is at least $C'f(n)$ for some instances.

Definition 3.2.3 (Θ notation). An algorithm is said to be $\Theta(f(n))$ if it is both $O(f(n))$ and $\Omega(f(n))$

Example. $\frac{1}{2}n^2 - 3n, \Omega(n^2) \leq \Theta(n^2) \leq O(n^2)$

Find c' and c (both > 0) where $c'n^2 \leq \frac{1}{2}n^2 - 3n \leq cn^2$ for a given $n_0, \forall n \geq n_0$ the inequality holds.

Let $c' = \frac{1}{14}$ and $c = \frac{1}{2}, \forall n \geq n_0$, where $n_0 = 7$, the inequality always holds.

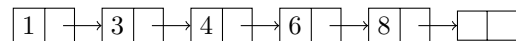
3.3 Representation of data

For set $\{1, 3, 4, 6, 8\}$ we have two ways to represent, array and list.

For array, the representation is

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 |

For list, the representation is



There is no "better" representation, one can be better than the other one in different cases.

Example. For \emptyset , array need to build a space with n cells of 0, complexity $O(n)$, list just need to build the first cell, $O(1)$

Example. To find if a number is in a set, array needs $O(1)$ (look at the address), list needs $O(n)$ (loop through list, worst case, entire list)

3.4 Size of a problem

Number of bits needed to store the problem

Example. Let $0 \leq A_{ij} \leq 2^{51}$

Representation by the bits of the number, $A_{ij} \leq 2^{51}$ can be represented by max of $O(\log(A_{ij}))$, (51 bits)

For matrix addition that the total storage for addition two matrix is $O(mnk)$, $k = O(\log|A_{mn}|)$

- strongly poly time

Example. $O(n^3.5)$

- pseudo-poly time

Example. $O(mn + C)$, $O(Cn)$

3.5 P and NP

- P
- Co-P
- NP
- Co-NP: The class of decision problems for which a yes response corresponds to a no for answering member of NP.

Example. Given a TSP, we ask does there **not** exist a tour?

Conjecture 1.

$$P \neq NP \quad (3.1)$$

Definition 3.5.1 (polynomial reduction). We say a problem A polynomially reduces to problem B, if we can transform problem A into problem B in polynomial number of steps so that if solve B in poly time ,we can reconstruct solution to A in poly time.

Definition 3.5.2 (NP-hard). Problems to which all members of NP reduces to. If one of those problem can be solved in poly time, we prove that $P = NP$.

Definition 3.5.3 (NPC). Decision problems that belong to NP-hard.

Here are some relations between different classes of problems

- $NP \subset DP$
- $P \subset NP$
- $P \subset NP \cup Co - NP$
- $NP - complete = NP \cup NP - hard$
- $Undecide \cup NP = \emptyset$

Given n, m number of variables and constants. As well as the largest const C of a problem:

- All algorithm will run in poly time if the number of guess is a poly function

Example. $O(mn)$, $O(m + n \log C)$

Chapter 4

Minimum Spanning Tree Problem

4.1 Basic Concepts

Example. A company wants to build a communication network for their offices. For a link between office v and office w , there is a cost c_{vw} . If an office is connected to another office, then they are connected to with all its neighbors. Company wants to minimize the cost of communication networks.

Definition 4.1.1 (Cut vertex). A vertex v of a connected graph G is a **cut vertex** if $G \setminus v$ is not connected.

Definition 4.1.2 (Connection problem). Given a connected graph G and a positive cost C_e for each $e \in E$, find a minimum-cost spanning connected subgraph of G . (Cycles all allowed)

theorem 4.1. An edge $e = uv \in G$ is an edge of a cycle of G iff there is a path $G \setminus e$ from u to v .

Definition 4.1.3 (Minimum spanning tree problem). Given a connected graph G , and a cost $C_e, \forall e \in E$, find a minimum cost spanning tree of G

The only way a connection problem will be different than MSP is if we relax the restriction on $C_e > 0$ in the connection problem.

4.2 Algorithms for Solving MSP

Algorithm 5 Kroskal Algorithm $O(m \log m)$

Require: A connected graph

Ensure: A MST

Keep a spanning forest $H = (V, F)$ of G , with $F = \emptyset$
while $|F| < |V| - 1$ **do**
 add to F a least-cost edge $e \notin F$ such that H remains a forest.
end while

- Kroskal start with a forest that contains all vertices, Prim start with a tree that only contain one vertex.

Algorithm 6 Prim Algorithm $O(nm)$

Require: A connected graph

Ensure: A MST

Keep $H = (V(H), T)$ with $V(H) = \{v\}$, where $r \in V(G)$ and $T = \emptyset$

while $|V(T)| < |V|$ **do**

 Add to T a least-cost edge $e \notin T$ such that H remains a tree.

end while

- Kroskal cannot guarantee every step it is a tree but can guarantee it is spanning, Prim can guarantee every step it is a tree but cannot guarantee spanning.

Definition 4.2.1 (cut). For a graph $G = (V, E)$ and $A \subseteq V$ we denote $\delta(A) = \{e \in E : e \text{ has an end in } A \text{ and an end in } V \setminus A\}$. A set of the form $\delta(A)$ for some A is called a **cut** of G .

Definition 4.2.2. We also define $\gamma(A) = \{e \in E : \text{both ends of } e \text{ are in } A\}$

Theorem 4.2. A graph $G = (V, E)$ is connected iff there is no $A \subseteq V$ such that $\emptyset \neq A \neq V$ with $\delta(A) = \emptyset$

Definition 4.2.3. Let us call a subset $A \subseteq E$ **extendible** to a minimum spanning tree problem if A is contained in the edge set of some MST of G

Theorem 4.3. Suppose $B \subseteq E$, that B is extendible to an MST and that e is a minimum cost edge of some cut D satisfying $D \cap B = \emptyset$, then $B \cup \{e\}$ is extendible to an MST.

4.3 Solve MST in LP

Given a connected graph $G = (V, E)$ and a cost on the edges C_e for all $e \in E$, Then we can formulate the following LP

$$X_e = \begin{cases} 1, & \text{if edge } e \text{ is in the optimal solution} \\ 0, & \text{otherwise} \end{cases} \quad (4.1)$$

The formulation is as following

$$\min \sum_{e \in E} c_e x_e \quad (4.2)$$

$$\text{s.t.} \quad \sum_{e \in E} x_e = |V| - 1 \quad (4.3)$$

$$x_e \geq 0 \quad (4.4)$$

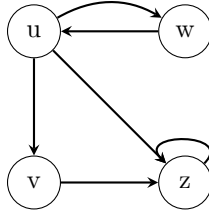
$$e \in E \quad (4.5)$$

$$\sum_{e \in E(S)} x_e = |S| - 1, \forall S \subseteq V, S \neq \emptyset \quad (4.6)$$

$$(4.7)$$

Chapter 5

Shortest-Path Problem



$$\begin{bmatrix} -1 & 0 & -1 & -1 & 1 \\ 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & -1 \\ 0 & 1 & 1 & 0 & 0 \end{bmatrix} \quad (5.2)$$

5.1 Directed Graph

Definition 5.1.1. A graph $G = (V, E)$ is called directed if for each edge $e \in E$, there is a **head** $h(e) \in V$ and a **tail** $t(e) \in V$ and the edges of e are precisely $h(e)$ and $t(e)$, denoted $e = (t(e), h(e))$

Definition 5.1.2. We call directed graphs **digraphs**, we call edges in a digraph are called **arcs**, and vertices in a digraph **nodes**

Definition 5.1.3. Similar as in the undirected case we have walks, traces, paths and cycles in digraphs.

Definition 5.1.4. A vertex $v \in V$ is **reachable** from a vertex $u \in V$ if there is a (u, v) -dipath. If at the same time u is reachable from v , they are **strongly connected**

Definition 5.1.5. A digraph is strongly connected if every pair of vertices are strongly connected.

Definition 5.1.6. A digraph is **strict** if it has no loops and whenever e and f are parallel, $h(e) = t(f)$

Definition 5.1.7. For a vertex v in a digraph D , the **indegree** of v in D , denoted by $d^+(v)$ is the number of arcs of D having head V . The **outdegree** of v is denoted by $d^-(v)$ is the number of arcs of D having tail v .

Let $D = (V, A)$ be a digraph with no loops a vertex-arc **incident matrix** for D is a $(0, 1, -1)$ matrix N with rows indexed by $V = \{v_1, \dots, v_n\}$ and column indexed by $A = \{e_1, \dots, e_m\}$ and where entry (i, j) in the matrix n_{ij} is

$$n_{ij} = \begin{cases} 1, & \text{if } v_i = h(e_j) \\ -1, & \text{if } v_i = t(e_j) \\ 0, & \text{otherwise} \end{cases} \quad (5.1)$$

5.2 Basic Concepts

- **INPUT** a digraph G a node $r \in V$, and if cost c_e for all $e \in E$
- **OUTPUT** find for each $v \in V$ a dipath from r to v of least cost (if cost exists).

All Shortest-Path methods are based on the same concept, suppose we know there exists a dipath from r to v of a cost y_v . For each vertex $v \in V$ and we find an arc $(v, w) \in E$ satisfying $y_v + c_{vw} < y_w$. Since appending (v, w) to the dipath to v takes a cheaper dipath to w then we can update y_w to a lower cost dipath.

So if the following property holds for all vertices we have found the least cost dipath from r to all vertices

$$y_v + c_{vw} \geq y_w \quad \forall (v, w) \in E \quad (5.3)$$

We call $y = (y_v : v \in V)$ a feasible potential if it satisfies that and $y_r = 0$

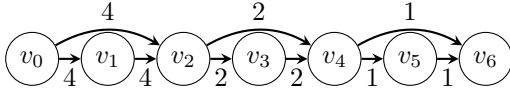
Proposition 1. *Feasible potential provides lower bound for the shortest path cost.*

Proof. Suppose that you have a dipath $P = v_0 e_1 v_1, \dots, e_k v_k$ where $v_0 = r$ and $v_k = v$, then

$$C(P) = \sum_{i=1}^k C_{e_i} \geq \sum_{i=1}^k (y_{v_i} - y_{v_{i-1}}) = y_{v_k} - y_{v_0} \quad (5.4)$$

□

Property of previous proposition provides a condition for a shortest path algorithm.



5.3 Ford's algorithm

We will initialize the algorithm with $y_r = 0$ and $y_v = \infty, v \in V \setminus r$

For the reason to recreate the shortest diath we will keep a predecessor function $P(w) \forall w \in V$ and set $P(w)$ to v whenever y_w is set to $y_v + c_{vw}$

If an arc (v, w) violates $y_v + c_{vw} \geq y_w$ we call it incorrect.

To correct (v, w) means to set $y_w = y_v + c_{vw}$ and to set $P(w) = v$

To initialize we set

$$y_r = 0, y_v = \infty, \forall v \in V \setminus r \quad (5.5)$$

$$P(r) = 0, P(v) = -1, \forall v \in V \setminus r \quad (5.6)$$

While y is not a feasible potential find incorrect arc (v, w) and correct it.

This algorithm is not perfect. If there is a cycle with minus total weight, it will never stop.

Here is another example that could take $O(2^n)$ to solve.

5.4 Ford-Bellman Algorithm

Algorithm 7 Ford-Bellman Algorithm

Ensure: Minimum spanning tree

Require: Connected tree

Initialize y and P

$i \leftarrow 0$

while $i < n$ and y is not a feasible potential **do**

$i++$

for $e \in E$ **do**

if e is incorrect **then**

 correct e

end if

end for

end while

(Only correct the node that comes from a node that has been corrected.)

A usual representation of a diagraph is to store all the arcs having tail v in a list L_v to **scan** v means the following:

- For $(v, w) \in L_v$, if (v, w) is incorrect, then correct (v, w)

For Bellman, will either terminate with shortest path from r to all $v \in V \setminus r$ or it will terminate stating that there is a negative cycle. In $O(mn)$

In the alogrithm if $i = n$ and there exists a feasible potential, the problem has a negative cycle.

(Finding a negative cycle in graph is NP hard???)

5.5 Acyclic Graphs

Suppose that the nodes of G can be ordered from left to right so that all arcs go from left to right. That is suppose there is an ordering $v_1, v_2, \dots, v_n \in V$ so that $(v_i, v_j) \in E$ implies $i < j$. We call such an ordering **topological** sort.

If we order E in the sequence that $v_i v_j$ precedes $v_k v_i$ if $i < k$ based on topological order then ford algorithm will terminate in one pass.

5.6 Dijkstra Algorithm

Algorithm 8 Dijkstra Algorithm

Ensure: Minimum spanning tree

Require: Connected tree

Initialize y and P

$S \leftarrow V$

while $S \neq \emptyset$ **do**

 Choose $v \in S$ with minimum y_v

$S \leftarrow S \setminus v$

 Scan v

end while

5.7 All pairs shortest path problem

If all weights/distances in the graph are nonnegative then we could use dijkstra withn starting nodes being eac one of the vertices of the graph. This method will take $O(n^3)$

If weight/distances are arbitrary and we would like to find shortest path beteen all pairs of vertices or detect a negative ccle we could use Bellman-Ford Algorithm with $O(n^4)$

We would like an algorithm to find shortest path between any two pairs in a graph for arbitrary weights (determined, negative, cycles) in $O(n^3)$

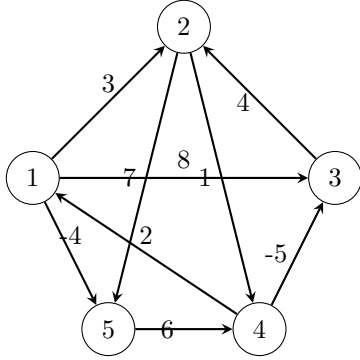
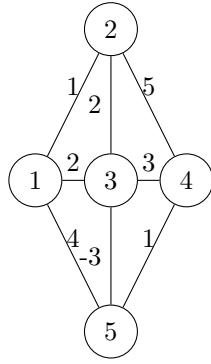
Let d_{ij}^k denote the length of the shortest path from i to j such that all intermediate vertices are contained in the set $\{1, \dots, k\}$

In this case $d_{14}^5 = 5$

If the vertex k is not an intermediate vertex on p , then $d_{ij}^k = d_{ij}^{k-1}$, notice that $d_{15}^4 = -1$, node 4 is not intermediate, so $d_{15}^3 = -1$

If the vertex k is an intermediate on p , then $d_{ij}^k = d_{ik}^{k-1} + d_{kj}^{k-1}$, $d_{14}^5 = 0$ ($p = 1 \rightarrow 3 \rightarrow 5 \rightarrow 4$), i.e., $d_{14}^5 = d_{15}^4 + d_{54}^4 = 0$

Therefore $d_{ij}^k = \min\{d_{ij}^{k-1}, d_{ik}^{k-1} + d_{kj}^{k-1}\}$



5.8 Floyd-Warshall Algorithm

Input: graph $G = (V, E)$ with weight on edges Output: Shortest path between all pairs of vertices on existence of a negative cycle Step1: Initialzie

$$d_{ij}^0 = \begin{cases} c_{ij} & \text{distance from } i \text{ to } j \text{ if } (i, j) \in E \\ 0 & \text{if } i = j \\ \infty & \text{if } (i, j) \notin E \end{cases} \quad (5.7)$$

Step2: For $k = 1$ to n For $i = 1$ to n For $j = 1$ to n $d_{ij}^k = \min\{d_{ij}^{k-1}, d_{ik}^{k-1} + d_{kj}^{k-1}\}$ Next j Next i Next k
Between optimal matrix D^n

$$D^0 = \begin{bmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & \infty & -5 & 0 & \infty \\ \infty & \infty & \infty & 6 & 0 \end{bmatrix} \quad (5.8)$$

$$\Pi^0 = \begin{bmatrix} & 1 & 1 & & 1 \\ & & & 2 & 2 \\ & 3 & & & \\ 4 & & 4 & & \\ & & & 5 & \end{bmatrix} \quad (5.9)$$

$$D^1 = \begin{bmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & \mathbf{5} & -5 & 0 & \mathbf{-2} \\ \infty & \infty & \infty & 6 & 0 \end{bmatrix} \quad (5.10)$$

$$\Pi^1 = \begin{bmatrix} & 1 & 1 & & 1 \\ & & & 2 & 2 \\ & 3 & & & \\ 4 & \mathbf{1} & 4 & & \mathbf{1} \\ & & & 5 & \end{bmatrix} \quad (5.11)$$

$$D^2 = \begin{bmatrix} 0 & 3 & 8 & 4 & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \mathbf{5} & \mathbf{11} \\ 2 & 5 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{bmatrix} \quad (5.12)$$

$$\Pi^2 = \begin{bmatrix} & 1 & 1 & \mathbf{2} & 1 \\ & & & 2 & 2 \\ & 3 & & \mathbf{2} & \mathbf{2} \\ 4 & 1 & 4 & & 1 \\ & & & 5 & \end{bmatrix} \quad (5.13)$$

$$D^3 = \begin{bmatrix} 0 & 3 & 8 & 4 & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & 5 & 11 \\ 2 & \mathbf{-1} & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{bmatrix} \quad (5.14)$$

$$\Pi^3 = \begin{bmatrix} & 1 & 1 & 2 & 1 \\ & & & 2 & 2 \\ & 3 & & 2 & 2 \\ 4 & \mathbf{3} & 4 & & 1 \\ & & & 5 & \end{bmatrix} \quad (5.15)$$

$$D^4 = \begin{bmatrix} 0 & 3 & \mathbf{-1} & 4 & -4 \\ \mathbf{3} & 0 & \mathbf{-4} & 1 & \mathbf{-1} \\ \mathbf{7} & 4 & 0 & 5 & \mathbf{3} \\ 2 & -1 & -5 & 0 & -2 \\ \mathbf{8} & \mathbf{5} & 1 & 6 & 0 \end{bmatrix} \quad (5.16)$$

$$\Pi^4 = \begin{bmatrix} & 1 & \mathbf{4} & 2 & 1 \\ \mathbf{4} & & \mathbf{4} & 2 & \mathbf{1} \\ \mathbf{4} & 3 & & 2 & \mathbf{1} \\ 4 & 3 & 4 & & 1 \\ \mathbf{4} & \mathbf{3} & \mathbf{4} & 5 & \end{bmatrix} \quad (5.17)$$

$$D^5 = \begin{bmatrix} 0 & \mathbf{1} & \mathbf{-3} & \mathbf{2} & -4 \\ 3 & 0 & -4 & 1 & -1 \\ 7 & 4 & 0 & 5 & 3 \\ 2 & -1 & -5 & 0 & -2 \\ 8 & 5 & 1 & 6 & 0 \end{bmatrix} \quad (5.18)$$

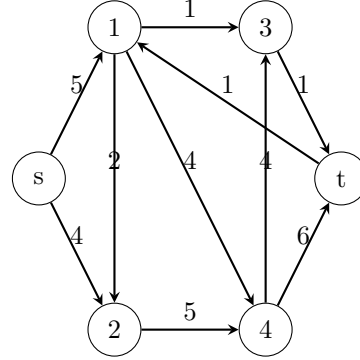
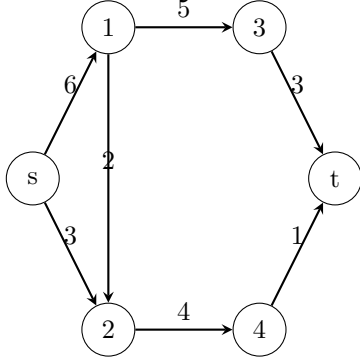
$$\Pi^5 = \begin{bmatrix} & \mathbf{3} & 4 & \mathbf{5} & 1 \\ 4 & & 4 & 2 & 1 \\ 4 & 3 & & 2 & 1 \\ 4 & 3 & 4 & & 1 \\ 4 & 3 & 4 & 5 & \end{bmatrix} \quad (5.19)$$

Time complexity $O(n^3)$

If during the previous processes, there exist an element of negative value in the diagonal, it means there exists negative cycle.

Chapter 6

Maximum Flow Problem



6.1 Maximum Flow

Let $D = (V, A)$ be a strict digraph with distinguished vertices s and t . We call s the source and t the sink, let $\mu = \{\mu_e : e \in A\}$ be a nonnegative integer-valued capacity function defined on the arcs of D . The maximum flow problem on (D, s, t, μ) is the following Linear program.

$$\max \quad v \quad (6.1)$$

$$\text{s.t.} \quad \sum_{h(e)=i} x_e - \sum_{t(e)=i} x_e = \begin{cases} -v, & \text{if } i = s \\ v, & \text{if } i = t \\ 0, & \text{otherwise} \end{cases} \quad (6.2)$$

$$0 \leq x_e \leq \mu_e, \quad \forall e \in A \quad (6.3)$$

We think of x_e as being the flow on arc e . Constraint says that for $i \neq s, t$ the flow into a vertex has to be equal to the flow out of vertex. That is, flow is conserved at vertex i for $i = s$ and for $i = t$ the net flow in the entire digraph must be equal to v . An x that satisfied the above constraints is an (s, t) -flow of value v . If in addition it satisfies the bounding constraints, then it is a feasible (s, t) -flow. A feasible (s, t) -flow that has maximum v is optimal on maximum.

6.2 The main theorem

Theorem 6.1. For $S \subseteq V$ we define (S, \bar{S}) to be a (s, t) -cut if $s \in S$ and $t \in \bar{S} = V - S$, the capacity of the cut, denoted $\mu(S, \bar{S})$ is $\sum \{\mu_e : e \in \delta^-(S)\}$ where $\delta^-(S) = \{e \in A : t(e) \in S \text{ and } h(e) \in \bar{S}\}$

Example. $S = \{1, 2, 3, s\}$, $\bar{S} = \{4, t\}$
 $\delta^-(S) = \{(2, 4), (3, t)\} \Rightarrow \mu(S, \bar{S}) = 7$

Definition 6.2.1. If (S, \bar{S}) has minimum capacity of all (s, t) -cuts, then it is called **minimum cut**.

Definition 6.2.2. Let $\delta^+(S) = \delta^-(V - S)$

Example. Let $S = \{s, 1, 2, 3\}$, $\bar{S} = \{4, t\}$, $u(S, \bar{S}) = u_{14} + u_{24} + u_{3t} = 10$, $\delta^-(S) = \{(1, 4), (2, 4), (3, t)\}$, $\delta^+S = \{(t, 1)\}$

theorem 6.2. If x is a (s, t) flow of value v and (S, \bar{S}) is a (s, t) -cut, then

$$v = \sum_{e \in \delta^-(S)} x_e - \sum_{e \in \delta^+(S)} x_e \quad (6.4)$$

Proof. Summing the first set of constraints over the vertices of S ,

$$\sum_{i \in S} \left(\sum_{h(e)=i} x_e - \sum_{t(e)=i} x_e \right) = -v \quad (6.5)$$

Now for an arc e with both ends in S , x_e will occur twice once with a positive and once with negative so they cancel and the above sum is reduced to

$$\sum_{e \in \delta^+(S)} x_e - \sum_{e \in \delta^-(S)} x_e = -v \quad (6.6)$$

□

Notice: Flow is the prime variable, capacity is the dual.

Corollary 6.2.1. *If x is a feasible flow of value v , and (S, \bar{S}) is an (s, t) -cut, then*

$$v \leq u(S, \bar{S}) \quad (\text{Weak duality}) \quad (6.7)$$

Definition 6.2.3. Define an arc e to be **saturated** if $x_e = u_e$, and to be **flowless** if $x_e = 0$

Corollary 6.2.2. *Let x be a feasible flow and (S, \bar{S}) be a (s, t) -cut, if $\forall e \in \delta^-(S)$ is saturated, and $\forall e \in \delta^+(S)$ is flowless, then x is a maximum flow and (S, \bar{S}) is a minimum cut. (Strong duality)*

Proof. If every arc of $\delta^-(S)$ is saturated then

$$\sum_{e \in \delta^-(S)} x_e = \sum_{e \in \delta^-(S)} u_e \quad (6.8)$$

If every arc of $\delta^+(S)$ is flowless then

$$\sum_{e \in \delta^+(S)} x_e = 0 \quad (6.9)$$

$\Rightarrow x$ is as large as it can get when $u(S, \bar{S})$ is as small as it can get. \square

Definition 6.2.4. Let P be a path, (not necessarily a dipath), P is called **unsaturated** if every **forward** arc is unsaturated ($x_e < u_e$) and ever **reverse** arc has positive flow ($x_e > 0$). If in addition P is an (s, t) -path, then P is called an **x-augmenting path**

Theorem 6.3. *A feasible flow x in a digraph D is maximum iff D has augmenting paths.*

Proof. (Prove by contradiction)

(\Rightarrow) Let x be a maximum flow of value v and suppose D has an augmenting path. Define in P (augmenting path):

$$D_1 = \min\{u_e - x_e : e \text{ forward in } P\} \quad (6.10)$$

$$D_2 = \min\{x_e : e \text{ backward in } P\} \quad (6.11)$$

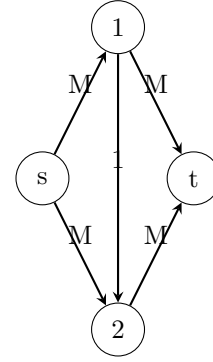
$$D = \min\{D_1, D_2\} \quad (6.12)$$

Since P is augmenting, then $D > 0$, let

$$\hat{x}_e = \begin{cases} x_e + D & \text{If } e \text{ is forward in } P \\ x_e - D & \text{If } e \text{ is backward in } P \\ x_e & \text{otherwise} \end{cases} \quad (6.13)$$

It is easy to see that \hat{x} is feasible flow and that the value is $V + D$, a contradiction.

(\Leftarrow) Suppose D admits no x-augmenting path, Let S be the set of vertices reachable from s by x-unsaturated path clearly $s \in S$ and $t \notin S$ (because otherwise there would be an augmenting path). Thus, (S, \bar{S}) is a (s, t) -cut.



Let $e \in \delta^-(S)$ then e must be saturated. For otherwise we could add the $h(e)$ to S

Let $e \in \delta^+(S)$ then e must be flow less. For otherwise we could add the $t(e)$ to S .

According to previous corollary, that x is maximum. \square

Theorem 6.4. (Max-flow = Minimum-cut) *For any digraph, the value of a maximum (s, t) -flow is equal to the capacity of a minimum (s, t) -cut*

6.3 Maximum flow algorithm

Finding augmenting paths is the key of max-flow algorithm, we need to describe two functions, labeling and scanning a vertex.

A vertex is first labeled if we can find x-unsaturated path from s , i.e., (s, v) -unsaturated path.

The vertex v is scanned after we attempted to extend the x-unsaturated path.

Algorithm 9 Labeling algorithm (Incorrect, need to be fixed)

Ensure: Max-flow x with value v

Require: Digraph with source s and sink t , a capacity function u and a feasible flow (could be $x_e = 0$)

Initialize, $v \leftarrow x$

Designate all vertices as unlabeled and unscanned

Label s

while There exists vertex unlabeled or unscanned **do**

Let i be such a vertex, for each arc e with $t(e) = i$, $x_e < u_e$ and $h(e)$ unlabeled, label $h(e)$

For each arc e with $h(e) = i$, $x_e > 0$ and $t(e)$ unlabeled, label $t(e)$, designate i as scanned.

If t is not label

end while

x is the maximum.

Labeling algorithm can be exponential, the following is an example

6.4

Chapter 7

Minimum Cost Flow Problem

Chapter 8

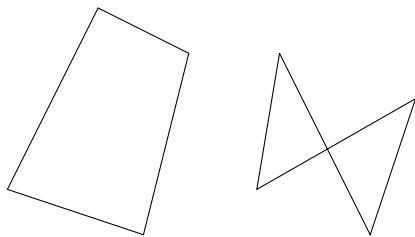
Assignment and Matching Problem

Chapter 9

Polygon Triangulation

9.1 Types of Polygons

Definition 9.1.1 (simple polygon). A **simple polygon** is a closed polygonal curve without self-intersection.

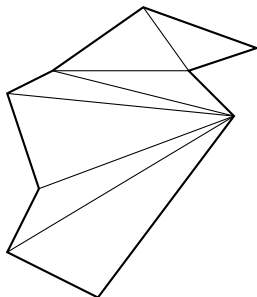


Simple Polygon Non-simple Polygon

Polygons are basic building blocks in most geometric applications. It can model arbitrarily complex shapes, and apply simple algorithms and algebraic representation/manipulation.

9.2 Triangulation

Definition 9.2.1 (Triangulation). **Triangulation** is to partition polygon P into non-overlapping triangles using diagonals only. It reduces complex shapes to collection of simpler shapes. Every simple n -gon admits a triangulation which has $n - 2$ triangles.



Triangulation

Theorem 9.1. *Every polygon has a triangulation*

theorem 9.2. *Every polygon with more than three vertices has a diagonal.*

Proof. (by Meisters, 1975) Let P be a polygon with more than three vertices. Every vertex of a P is either *convex* or *concave*. W.L.O.G. (any polygon must has convex corner) Assume p is a convex vertex. Denote the neighbors of p as q and r . If $\bar{q}r$ is a diagonal, done, and we call $\triangle pqr$ is an *ear*. If $\triangle pqr$ is not an ear, it means at least one vertex is inside $\triangle pqr$, assume among those vertices inside $\triangle pqr$, s is a vertex closest to p , then $\bar{p}s$ is a diagonal. \square

9.3 Art Gallery Theorem

Theorem 9.3. *Every n -gon can be guarded with $\lfloor \frac{n}{3} \rfloor$ vertex guards*

theorem 9.4. *Triangulation graph can be 3-colored.*

Problem 9.1. The floor plan of an art gallery modeled as a simple polygon with n vertices, there are guards which is stationed at fixed positions with 360 degree vision but cannot see through the walls. How many guards does the art gallery need for the security? (Fun fact: This problem was posted to Vasek Chvatal by Victor Klee in 1973).

Proof. - P plus triangulation is a planar graph
- 3-coloring means there exist a 3-partition for vertices that no edge or diagonal has both endpoints within the same set of vertices.

- Proof by Induction:

- Remove an ear (there will always exist ear)
- Inductively 3-color the rest
- Put ear back, coloring new vertex with the label not used by the boundary diagonal. \square

9.4 Triangulation Algorithms

Part II

Nonlinear Programming

Chapter 10

Introduction and Motivation

10.1 Basic concept

$$\min f(x) \quad (10.1)$$

$$\text{s.t. } g_i(x) \leq 0, \quad \forall i = 1, \dots, m \quad (10.2)$$

$$h_i(x) = 0, \quad \forall i = 1, \dots, m \quad (10.3)$$

$$x \in X \quad (10.4)$$

Iso-value curve

Given a function $f(x) : R^n \rightarrow R$, the iso-value curve of level k , denoted by L_k is the set of points for which $f(x) = k$, Formally,

$$L_k = \{x \in R^n | f(x) = k\} \quad (10.5)$$

Observations:

- An optimization problem may not have a feasible solution

- Even if the problem has a feasible solution, the problem may not have an optimal solution

- If an optimal solution exists, then

- if may be unique - it may be a convex set -

it may be several sets

The following two problems are equivalent

$$\min x_1 + x_2 \quad (10.6)$$

$$\text{s.t. } x_1 + 2x_2 \leq 3 \quad (10.7)$$

$$x_1, x_2 \in \{0, 1\} \quad (10.8)$$

and

$$\min x_1 + x_2 \quad (10.9)$$

$$\text{s.t. } x_1 + 2x_2 \leq 3 \quad (10.10)$$

$$x_1 \geq 0 \quad (10.11)$$

$$x_2 \geq 0 \quad (10.12)$$

$$x_1(1 - x_1) = 0 \quad (10.13)$$

$$x_2(1 - x_2) = 0 \quad (10.14)$$

10.2 Traffic Assignment

10.3 Newsvendor Problem

Parameter

- for each newspaper, cost is \$c
- vendor determine the number of newspaper to buy as N
- each news paper sold for \$p
- each news paper has a salvage value of \$v
- for demand scenario $d_i, i \in N$, the probability is $\pi_i \in N$

Decision Vars

- number of newspaper to buy, q
- number of newspaper returned, $r_i, i \in N$
- number of newspaper sold, $s_i, i \in N$

Constraints

- $q = s_i + r_i$
- $s_i = \min\{d_i, q\}$
- $q \in Z_+ \cup \{0\}$
- $r_i, s_i \in Z_+ \cup \{0\}$

Objective Fuction

$$\max \sum_{i \in N} \pi_i (ps_i + vr_i) - cq \quad (10.15)$$

10.4 Portfolio Optimization

Parameters

- A , set of assets
- \bar{r} , desired portfolio's return
- r_i , expected return of $i \in A$
- σ_{ij}^2 , covariance between i and $j, i, j \in A$

Decision Vars

- x_i % of total budget to invest to asset $i \in A$

Constraints

- $\sum_{i \in A} x_i = 1$
- $\sum_{i \in A} \alpha_i x_i \geq \bar{r}$
- Nonnegativity

Objective function

$$\min \sum_{i \in A} \sum_{j \in A} \sigma_{ij}^2 x_i x_j \quad (10.16)$$

10.5 Curve Fitting

Chapter 11

Background

11.1 Real Vector Spaces

11.2 Linear Subspaces

11.3 Inner Products

11.4 Norms

Chapter 12

Convex Analysis

12.1

Chapter 13

KKT Optimality Conditions

Chapter 14

Lagrangian Duality

Chapter 15

Unconstrained Optimization

Chapter 16

Penalty and Barrier Functions