

# Divide and Conquer

## Multiplication

- Problem: Given two n-digit numbers x and y, compute their product.
- $T(n) = 3T(n/2) + O(n)$
- $T(n) = O(n^{\log_2 3})$
- 1:
 

```
2: function KARATSUBA(x, y)
3:   ▷ Append zeros to the left so that |x| = |y| = n = 2k
4:   if n = 1 then
5:     return xy
6:   ▷ Write x = a · 2n/2 + b and y = c · 2n/2 + d
7:   α ← Karatsuba(a, c)
8:   β ← Karatsuba(b, d)
9:   γ ← Karatsuba(a + b, c + d)
10:  return α · 2n + (γ - α - β) · 2n/2 + β
```

## Matrix Multiplication

- Magic Idea:

- $P_1 = A(F - H)$
- $P_2 = (A + B)H$
- $P_3 = (C + D)E$
- $P_4 = D(G - E)$
- $P_5 = (A + D)(E + H)$
- $P_6 = (B - D)(G + H)$
- $P_7 = (A - C)(E + F)$
- $XY = \begin{pmatrix} A & B \\ C & D \end{pmatrix} \begin{pmatrix} E & F \\ G & H \end{pmatrix}$

$$= \begin{pmatrix} P_5 + P_4 - P_2 + P_6 & P_1 + P_2 \\ P_3 + P_4 & P_1 + P_5 - P_3 - P_7 \end{pmatrix}$$

- $7^{\log_2 n}$  multiplications

## Sorting

- $O(n \log n)$  sorting algorithms

- Merge Sort
- Quick Sort
- Heap Sort

- $O(n^2)$  sorting algorithms

- Bubble Sort
- Selection Sort
- Insertion Sort

## Selection Problem

- Input: A set of n integers  $x_1, x_2, \dots, x_n$  and an integer k
- Output: The k-th smallest integer  $x^*$  among  $x_1, x_2, \dots, x_n$
- 1:
 

```
2: function SELECT(S, k)
3:   ▷ Choose a random value v in  $x_1, x_2, \dots$ 
4:   ▷ Divide  $x_1, x_2, x_3, \dots$  into three sets: L:  $x < v$ , M:  $x = v$ , R:  $x > v$ 
5:   if  $|L| \geq k$  then
6:     return Select(L, k)
7:   if  $|L| + |M| < k$  then
8:     return Select(R, k - |L| - |M|)
9:   return v
```

## Running Time:

- $\tau(n)$ : Time we reduce n to  $\frac{3n}{4}$
- $T(n) = \tau(n) + T(\frac{3n}{4})$
- $E[T(n)] = E[\tau(n)] + E[T(\frac{3n}{4})]$
- $E[\tau(n)] = O(n)$
- $E[T(n)] = O(n)$

## Medium of Medium

- Partition S into subsets of 5 elements
- find the medians of them
- Finding a good pivot takes  $O(n) + T(n/5)$  time.
- the subproblem size is at most  $\frac{7n}{10}$ .
- $T(n) = T(\frac{7n}{10}) + O(n) + T(\frac{n}{5}) = O(n)$

## Closest Pair

- Problem: Given n points in the plane, find the closest pair of points.
- Algorithm:
  1. Sort the points by x-coordinate
  2. Divide the points into two equal-sized sets by a vertical line  $x = x_{\text{mid}}$
  3. Find the closest pair in each set recursively, let  $d_l, d_r$  be the distance.
  4. let  $d = \min(d_l, d_r)$  and  $S'$  be the set of points at most  $d$  from the line.
  5. Sort the points in  $S'$  by y-coordinate
  6. For each point b, check 7 point above b, and find the closest pair.
  7. Return the closest pair.
- Running Time:  $O(n \log^2 n)$

## Master Theorem

Given constants  $a \geq 1, b > 1, d \geq 0$  and  $w \geq 0$ , if  $T(n) = 1$  for  $n < b$  and  $T(n) = aT(n/b) + n^d \log^w n$ , we have

$$T(n) = \begin{cases} O(n^d \log^w n) & \text{if } a < b^d \\ O(n^{\log_b a}) & \text{if } a > b^d \\ O(n^d \log^{w+1} n) & \text{if } a = b^d \end{cases}$$

## Graph

### DFS

Running time:  $O(V+E)$

- DFS Tree:
  - Undirected Graph:
    - Root: the first explored vertex
    - If we explore v from u, then v is u's child.
  - Two kinds of edges:
    - Tree edges
    - Back edges
- Directly Graph:
  - Four kinds of edges:
    - Tree edges
    - Back edges
    - Cross edges
    - Forward edges

### Application:

- Undirected Graph
  1. Reachability
  2. Connected Components(CC)
  3. T has back edges  $\leftrightarrow$  G has cycles.
- Directly Graph
  1. Topological Ordering (Directed Acyclic Graph, DAG).
    - Algorithm: sort vertices by descending order of finish time of DFS.  $O(|V|+|E|)$
  2. Strongly Connected Components(SCC)

#### Algorithm

- 1: Construct  $G^R$
- 2: DFS  $G^R$  with finish time
- 3: Choose v with the largest finish time
- 4: Explore(v) in G
- 5: When it returns, reached vertices form one SCC ( $|V_1|$ )
- 6: Remove them in both G and  $G^R$   $|V| \leftarrow |V| - |V_1|$   
 $|E| \leftarrow |E| - |\Delta E|$
- 7: Repeat from 2

#### Running Time: O()

#### Algorithm(Super Plan)

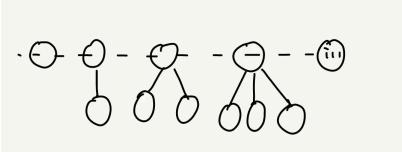
- 1: DFS G<sup>R</sup> and maintain a sorted list by the finish time.
- 2: DFS G by the descending order of the finish time
  1. Keep explore vertices by the descending order.
  2. Do not start from a reached vertex.
- 3: Each explore() forms a SCC.

To proof: Lemma: If SCC1 can reach SCC2 in  $G^R$ , then we have  $\max_{v \in \text{SCC1}} \text{finish}[v] > \max_{u \in \text{SCC2}} \text{finish}[u]$

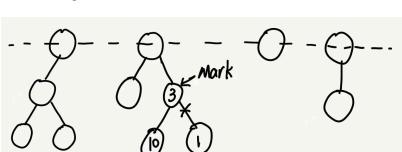
• Running Time:  $O(|V|+|E|)$

## Shortest Path

- BFS (no weights) and Dijkstra (weighted)
- Dijkstra Algorithm
  - Core Idea: explore the unvisited vertex with the smallest distance first.
  - Running Time:
    - simple array:  $O(V^2 + |E|)$
    - Binary Heap:  $O(V + E \log |V|)$
    - Fibonacci Heap:  $O(E + V \log |V|)$
    - Each degree at most has one root!



- The children of every vertex have the same degree property: Each degree at most has one root!
- We only allow each non-root node to lose one child.
- Max degree D is at most  $O(\log n)$ .
- Cascading Cut



- Amortized Analysis: Potential Function

$$\hat{C} = C + \delta \Delta \cdot \Phi$$

$$\Phi = t + 2m$$

$$t: \# \text{roots(extra)}, m: \# \text{marked nodes}.$$

• Update:

- $\hat{C} = O(\#\text{CC} + 1) + \delta(\Delta \Phi) = O(\#\text{CC} + 1) + \delta((\#\text{CC} + 1) + (-\#\text{CC} + 1)) = O(1)$
- Pop Min:  $\hat{C} = O(t^- + D) + \delta \Delta t \leq O(t^- + 2D) + \delta(D - t^-) = O(D) = O(\log n)$

## Shortest Path With Negative Weights

- Bellman-Ford Algorithm

- 1:
 

```
2: function BELLMAN_FORD(G, s)
3:   ▷ dist[s] = 0, dist[x] = ∞ for other x ∈ V
4:   while ∃ dist[x] is updated do
5:     for each (u, v) in E do
6:       dist[v] ← min{dist[v], dist[u] + d(u, v)}
7:   return "dist"
```
- Correctness:
  - Lemma1: After k rounds, dist(v) is the shortest distance of all k-edge-path
  - Lemma2: The shortest distance of all  $|V|$ -edge-path can not be shorter than the shortest distance of all  $(|V|-1)$ -edge-path unless there is a Negative Cycle.
- Running Time:
  - $O(|V||E|)$

## Greedy

### Minimum Spanning Tree

- Problem: Given a connected, undirected graph  $G = (V, E)$  with edge weights, find a minimum spanning tree.

- Prime & Kruskal

---

#### Algorithm 1: Prime's Algorithm

---

**Input:** A graph  $G = (V, E)$  with edge weights.

**Output:** A minimum spanning tree T.

- 1:  $T \leftarrow \{\}, S \leftarrow \{s\};$
- 2:  $\text{cost}[s] = 0, \text{cost}[v] \leftarrow \infty$  for all v other than s;
- 3:  $\text{cost}[v] \leftarrow w(s, v), \text{pre}[v] = s$  for all  $(s, v) \in E$ ;
- 4: Find  $v \notin S$  with smallest cost[v];
- 5:  $S \leftarrow S + \{v\}, T \leftarrow T + \{(\text{pre}[v], v)\}$
- 6:  $\text{cost}[u] = \min(\text{cost}[u], w(v, u))$  for all  $(v, u) \in E$
- 7: If  $\text{cost}[u]$  is updated, then  $\text{pre}[u] = v$ ;

• Running Time:  $|E|$  rounds Update,  $|V|$  rounds PopMin.  $O(|E| + |V| \log |V|)$  for Prime's Algorithm. With Fibonacci Heap, we can do better.

---

#### Algorithm 2: Kruskal's Algorithm

---

**Input:** A graph  $G = (V, E)$  with edge weights.

**Output:** A minimum spanning tree T.

- 1:  $T \leftarrow \{\}, S \leftarrow \{\};$
- 2: Sort edges in E by non-decreasing order of weights;
- 3: For each edge  $(u, v) \in E$ :
  1. If  $u \notin S$  or  $v \notin S$ , then  $T \leftarrow T + \{(u, v)\}, S \leftarrow S + \{u, v\}$ ;

• Running Time:  $O(E \log E) = O(E \log V)$  for Kruskal's Algorithm.

## Union Find Set (With Path Compression)

- Running Time Analysis (Amortized Analysis):
  - We prove: any m find operations totally cost  $O(m \log^* n + n \log^* n)$
  - Then we can say the amortized cost is  $O(\log^* n)$  for each find operation.
  - Lemma1: Parent's rank is strictly larger than the child.
  - Lemma2: The tree of v has at least  $2^{\text{rank}[v]}$  vertices.
  - Group vertices by rank: Group i:  $k_i = 2^{k_{i-1}}(1|2|3-4|5-16|17-65536|...)$
  - Across Group Charing (AGC)
  - Same Group Charging (SGC)
  - Lemma3: We have at most  $\log^* n$  groups.
  - Lemma4: Group  $[k+1, 2^k]$  at most have  $\frac{n}{2^k}$  vertices.
  - each find incurs at most  $\log^* n$  AGC.
  - for a vertex v, at most  $2^k - (k+1) < 2^k$  SGC for v.
  - In a group  $[k+1, \dots, 2^k]$ , at most  $\frac{n}{2^k} * 2^k = n$  SGC.
  - So, the total cost is  $O(m \log^* n + n \log^* n)$  for m find operations.

## Halfman code

The more frequent an encoding appears, the shorter the encoding is. Denote  $T$  as the Huffman Tree, and  $T'$  the tree that switched  $u, v$ , where  $\text{len}(u) < \text{len}(v)$ ,  $w(u) > w(v)$ .  $\text{avg\_len}(T) - \text{avg\_len}(T') = w(u)c \cdot \text{len}(u) + w(v)c \cdot \text{len}(v) -$

$$w(v)\text{len}(u) - w(u)\text{len}(v) = (w(u) - w(v))(\text{len}(u) - \text{len}(v)) < 0.$$

Next, we'll guarantee that every next step is optim, i.e.  $T_{\{i-1\}}$  is part of  $T$ . For base step... For inductive step: If we merge  $A$  and  $B$  in  $T$ . If  $A$  is paired with  $C$  in  $T^*$ , then  $w(C) > w(A)$ ,  $w(B)l = w(C)$ . If  $w(B) = w(C)$ , changing  $B$  and  $C$  preserves avg\_len. If  $w(B) < w(C)$ ,  $\text{len}(B) \geq \text{len}(C)$  by above proof. If  $\text{len}(B) == \text{len}(C)$ , swapping  $B$  and  $C$  also preserves avg\_len. If  $\text{len}(B) > \text{len}(C)$ ,  $D$  is not processed,  $w(D) > \max(w(A), w(B))$ , but  $\text{len}(D) = \text{len}(B) > \text{len}(C)$ , contradict with the fact that  $T^*$  is optimal(by above proof).

Another interpretation is by sorting inequality, namely, the sum of  $\sum$  ordered\_sequence  $\leq \sum$  random\_sequence  $\leq \sum$  inversed\_sequence.

textbf{time complexity:} By using binary-heap, every time we conduct pop twice to obtain the top two min vertice and a push to add the new parent vertice in the tree, which takes  $O(n \log n)$ .

## Makespan Minimization

- Greedy: Schedule jobs to the earliest finished machine.
- Greedy is at most 2 times of OPT in any input!
- LPT Algorithm:
  - Longest Processing Time First
  - Insert jobs into the earliest finished machine.
- Greedy is at most 4/3 times of OPT in any input!
- When  $\text{OPT} \geq 3p_n$ ,  $\text{ALG} = t + p_n < \frac{4}{3} \text{OPT}$
- When  $\text{OPT} < 3p_n$ 
  - Lemma 1: Every machine in OPT only has two jobs.
  - Lemma 2:  $p_1 \sim p_m$  are scheduled on different machines in OPT.
  - Lemma 3:  $p_m \sim p_n$  is correctly scheduled based on Lemma 1.
  - Lemma 4:  $\text{ALG} = \text{OPT}$  for  $p_1 \sim p_n$  if  $\text{OPT} < 3p_n$ .

## DP

### Guideline

1. find subproblem
2. check whether we are in a DAG and find the topological order of the DAG
3. solve & store subproblems by the topological order.

### Shortest path in DAG

$$\text{dist}(t) = \min \text{dist}(v) + \omega(v, t) \text{ for } (v, t) \text{ in E}$$

$O(V+E)$

## Longest Increasing Subsequence

### Algorithm 3: LIS

```
function LIS(n)
lis[0] = 0
for i = 1 to n
  lis[i] = maxaj < ai, j < i lis[j] + 1
return max1 ≤ i ≤ n lis[i]
```

### Using priority queue

$Sm[\text{len}]$  : the smallest ended number for an increasing subsequence with length  $\text{len}$ .

1.  $a_i > sm[\text{len}]$ : It can create a longer LIS, but can't update  $sm[\text{len}]$
2.  $a_i < sm[\text{len}]$ : It must update  $sm[\text{len}]$ , but can't create a longer LIS.

结合二分搜索, 复杂度为  $O(nlg n)$

### Edit Distance

Allow insertion Deletion and replacement  $ED[i, j]$  : The edit distance between  $X[1..i]$  and  $Y[1..j]$ .

$$ED[i, j] = \min \begin{cases} ED[i-1, j-1] + 1 \text{ if } x[i] \neq y[j] \\ ED[i-1, j] + 1 \\ ED[i, j-1] + 1 \end{cases}$$

### Knapsack Problems

Input:  $n$  items with cost  $c_i$  and value  $v_i$ , and a capacity  $W$ .

Output: Select a subset of items, with total cost at most  $W$ . The goal is to maximize the total value.

$$f[i, w] = \max\{f[i-1, w], f[i-1, w-c_i] + v_i\}$$

$$O(nW)$$

### Surplus Supply

Input:  $n$  items with cost  $c_i$  and value  $v_i$ , and a capacity  $W$ .

Output: Select some items (**each items can be selected more than once**), with total cost at most  $W$ . The goal is to maximize the total value

### Simple version

$f[w]$  : the maximum value we can with  $w$  budget.

### Algorithm 4: Surplus Supply

```
f[0] = ... = f[n] = 0
for w = 0 to W
  for i = 1 to n
    f[w] = max{f[w], f[w-ci] + vi}
return f[n, W]
```

### Transfer

1. Not but it anymore: can at most use  $w$  budget before  $i$ .
2. Buy: use at most  $w - c_i$  budget before  $i$  and  $i$

$$f[i, w] = \max\{f[i-1, w]\}, f[i, w - c_i] + v_i\}$$

### Largest Number in k Consecutive Numbers

#### Subproblem Definition

Input:  $\text{large}[i]$  : the largest number from  $a_i - k + 1$  to  $a_i$ .

Output:  $\text{large}[k]$  to  $\text{large}[n]$ .

#### Potential Largest List

- PLL[i]: the Potential Largest List for  $a_{i-k+1} \sim a_i$ ;
- At most  $k$  numbers
- Sorted by the index
- $a_i \geq a_j$  if  $i < j$
- $i-k+1 \leq \text{Index} \leq i$

### Algorithm 5: Updating Priority Queue

```
function updating(a[1..n], i, k, PLL)
  if PLL.front.index ≤ i-k
    PopFront()
    while PLL.back.value ≤ a[i]
      PopBack()
      PushBack(a[i])
  function largest(a[1..n], k)
    PLL = NULL
    for i = 1 to n
      updating(a, i, k, PLL)
    output PLL.front
```

### Time

The cost of  $n$  times updating has been charged to numbers!

Each number

- Charged once when it is popped out.
- Charged once when it is pushed in.

Totally:  $O(n)$ .

### Minimizing Manufacturing Cost

Input: A sequence of items with cost  $a_1, a_2, \dots, a_n$ .

- Operation  $\text{man}(l, r)$ : manufacture the items from  $l$  to  $r$ .

$$\text{cost}(l, r) = C + \left( \sum_{i=l}^r a_i \right)^2$$

Output: The minimum cost to manufacture all items

$y$  is better than  $x$  for  $i$  means the gradient of  $x$  to  $y$   $g(x, y)$  smaller than  $s(i)$ .  $s(i) = \sum_{k=1}^i a_k$

$$g(x, y) = \frac{f[y] + s^2(y) - f[x] + s^2(x)}{2(s(y) - s(x))}$$

### Algorithm 6: Convex hall

let  $j_1 \dots j_m$  be the convex hall

loop from  $k = m$  (charge to  $i$ )

while  $g(j_{k-1}, j_k) \geq g(j_k, i)$ (charge to  $j_k$ )

  kick  $j_k$

$k-$

Until  $g(j_{k-1}, j_k) \leq g(j_k, i)$ (charge to  $i$ )

$j_{k+1} = i$

### Algorithm 7: updating f[i]

let  $j_1 \dots j_m$  be the convex hall

loop from  $k = 1$

while  $g(j_k, j_{k+1}) \leq s(i)$ (charge to  $j_k$ )

  kick  $j_k$

$k+$

Until  $g(j_k, j_{k+1}) \geq s(i)$ (charge to  $i$ )

$j_k$  is best

$$f[i] = f[j] + C + \left( \sum_{k=j+1}^i a_k \right)^2 = f[j] + C + (s(i) - s(j))^2$$

### Product of Sets

Input:  $n$  sets  $L_n$  Output: The minimum number of operations to calculate  $L_1 \times \dots \times L_n$   $L_1 \times L_2 = \{(a, b) | a \in L_1, b \in L_2\}$

### Transfer

$$c(i, j) = m_i m_{i+1} \dots m_j + \min_{i \leq k < j} \{c(i, k) + c(k+1, j)\}$$

### Time Complexity

$$O(n^3)$$

### Quadrangle Inequality

$$\forall i \leq i' \leq j \leq j', w(i, j) + w(i', j') \leq w(i', j) + w(i, j')$$

### monotonicity

$$\forall i \leq i' \leq j \leq j', w(i', j) \leq w(i, j')$$

### Bellman-Ford

$dist[k, v]$  : the shortest distance from  $s$  to  $v$  among all  $k$ -edgepath (path with at most  $k$  edges)

### Algorithm 8: updating f[i]

```
function bellman(G, s)
dist[0, s] = 0, dist[0, x] = ∞ for other x in V
for k = 1 to |V|
  for each (u, v) in E dist[k, v] =
    min{dist[k-1, v], dist[k-1, u] + d(u, v)}
```

### All Pair Shortest Path

- Input: A directed graph  $G(V, E)$ , and a weighted function  $d(u, v)$  for all  $u, v \in E$ .
- Output: Distance  $dist(u, v)$ , for all vertex pair  $u, v$ .
- $V$  times Bellman-Ford  $O(V^2E)$

Floyd-Warshall:  $dist[k, u, v]$  : the shortest distance from  $u$  to  $v$  that only across inter-vertices in  $\{v_1, \dots, v_k\}$

We can label vertices from 1 to  $|V|$ .  $dist[|V|, u, v]$  is exactly what we want!

### Algorithm 9: Floyd-Warshall

```
function floyd_marshall(G)
dist[0, u, v] = d(u, v) for all u, v ∈ E, dist[0, u, v] = ∞ otherwise.
for k = 1 to |V|
  for u = 1 to |V|
    for v = 1 to |V|
      dist[k, u, v] = min{dist[k-1, u, v], dist[k-1, u, k] + dist[k-1, k, v]}
```

$O(V^3)$  running time but  $O(V^2)$  space

### Traveling Salesman Problem (TSP)

1. Input: A complete weighted undirected graph  $G$ , such that  $d(u, v) > 0$  for each pair  $u, v (u \neq v)$ .
2. Output: the cycle of  $n$  vertices with the minimum weight.

$f[S, u, v]$

- The shortest path from  $u$  to  $v$  with inter-vertex exactly  $S \subset V$  except  $u$  and  $v$ .
- $\min_u f[V, u, u]$  is what we want!

$$f[S, u, v] = \min_{k \in S} [S - \{k\}, u, k] + d(k, v)$$

### Time Complexity

$$n = |V|$$

- $O(n2^n)$  subproblems

- $O(n)$  solving

Brute-force:  $O(n!)$

### Maximize Independent Set on Trees

$$f[v] = \max\{\sum_{u \in \text{children}(v)} f[u], \sum_{u \in \text{grandchildren}(v)} f[u] + 1\}$$

Each of its children and its grandchildren cost one.

O(n)

### Greedy:

1. Choose all Leaves
2. Remove all leaves' parents
3. repeat 1

### 一些题目

注意证明拓扑性质

the number of vertex covers in G

$$f_u = \prod_{v \in \text{son}(u)} (f_v + g_v)$$
$$g_u = \prod_{v \in \text{son}(u)} f_v$$

the number of minimum vertex covers in G

(b) We calculate the following DP:  $f_i^*$ : the number of maximum independent set in the subtree of  $i$  when  $i$  is chosen,  $g_i^*$  for not chosen.  $fs_i^*$ : the size of maximum independent set in the subtree of  $i$  when  $i$  is chosen,  $gs_i^*$  for not chosen. The DP equation is

$$f_i^* = \prod_{v \in \text{son}(u)} \min(f_v^*, g_v^*, fs_v^*, gs_v^*)$$
$$g_i^* = \prod_{v \in \text{son}(u)} f_v^*$$

$$fs_u^* = \sum_{v \in \text{son}(u)} \min\{f_v^*, gs_v^*\} + 1$$
$$gs_u^* = \sum_{v \in \text{son}(u)} fs_v^*$$

where  $\min(f_v^*, g_v^*, fs_v^*, gs_v^*)$  is a function that

$$\min(f_v^*, g_v^*, fs_v^*, gs_v^*) = \begin{cases} f_v^*, & fs_v^* < gs_v^* \\ g_v^*, & fs_v^* > gs_v^* \\ f_v^* + g_v^*, & fs_v^* = gs_v^* \end{cases}$$

### Network Flow

二分图是可以被二着色的图 如果流有下限，可以构造一个新的图， $s'$ 到 $u$ 为到 $u$ 的下限的和，出边同理，边的capacity为上界减下界来确定是否有 feasible，如果有 feasible，可以push一次 feasible后在 $G_f$ 上寻找最大流

### Algorithm

$G_f = (V_f, E_f)$  is defined as:  $V_f = V \setminus \{u, v\} \in E_f$  if one of the following holds

- $(u, v) \in E$  and  $f(u, v) < c(u, v)$ : in this case,  $c^f(u, v) = c(u, v) - f(u, v)$
- $(v, u) \in E$  and  $f(v, u) > 0$ : in this case,  $c^f(u, v) = f(v, u)$

### Algorithm 10: Network-Flow

Initialize an empty flow  $f$  and the corresponding residual flow  $G_f$

Iteratively

    find a path on  $G_f$ ,

    push maximum amount of flow on  $G_f$ , and

    update  $f$  and  $G_f$ ,

until there is no s-t path on  $G_f$ .

### Algorithm 11: FordFulkerson

FordFulkerson( $G = (V, E)$ ,  $s, t, c$ ):

- ```
1 initialize f such that  $\forall e \in E: f(e) = 0$ ; initialize  $G' \leftarrow G$ ;
2 while there is an s-t path p on  $G'$ :
3     find an edge e  $\in p$  with minimum capacity b;
4     for each e =  $(u, v) \in p$ :
5         if  $(u, v) \in E$ : update  $f(e) \leftarrow f(e) + b$ ;
6         if  $(v, u) \in E$ : update  $f(e) \leftarrow f(e) - b$ ;
7     endfor
8     update  $G'$ ;
9 endwhile
10 return f
```

### Time Complexity

#### All the capacities are integers

**Lemma 1.** Each while-loop iteration increase the value of  $f$  by at least 1. **Lemma 2.** If each  $c(e)$  is an integer, then the max flow  $f_{max}$  is an integer.

$O(Ef_{max})$

**Theorem.** If each  $c(e)$  is an integer, then the value of the maximum flow  $f$  is an integer.

#### Correctness: Max-Flow-Min-Cut Theorem.

The value of the maximum flow is exactly the value of the minimum cut:

$$\max_f v(f) = \min_{L, R} c(L, R)$$

$$c(L, R) = \sum_{(u, v) \in E, u \in L, v \in R} c(u, v)$$

proof

$$\text{Claim } v(f) = f_{ou}(L) - f_{in}(L)$$

For a cut L and R of the original graph

$$f_{in}(L) = \sigma_{u, v \in E, u \in L, v \in R} f(v, u)$$

$$v(f) = f_{ou}(L) - f_{in}(L)$$

$$f_{ou}(u) = f_{in}(u) \text{ for } u \in V \setminus \{s, t\}, f_{ou}(s) = v(f), f_{in}(s) = 0$$

$$v_f = \sum_{u \in L} (f_{ou}(u) - f_{in}(u)) = f_{ou}(L) - f_{in}(L)$$

**Lemma 1.** For any flow  $f$  and any cut  $\{L, R\}$  in  $G$ , we have  $v(f) \leq c(L, R)$ .

$L$ : reachable from  $s$  in  $G_f$ ,  $f_{ou}(L) = c(L, R), f_{in}(L) = 0$

**Lemma 2.** There exists a cut  $\{L, R\}$  such that the flow  $f$  output by Ford-Fulkerson Algorithm satisfies  $v(f) = c(L, R)$ .

• Hall's Marriage Theorem. There exists a matching of size  $|A|$  if and only if  $|S| \leq |N(S)|$  for every  $S \subseteq A$ .

### More Applications

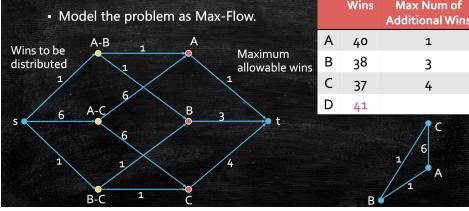
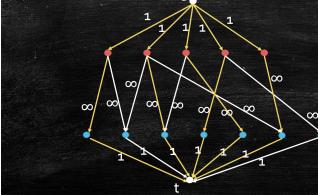


Figure 2: 比赛问题

### Application 2: Maximum Bipartite Matching

• An integral flow corresponds to a matching.

• Integrality theorem ensures the maximum flow can be integral.



### Algorithm for finding a minimum cut

**Min-Cut Problem:** Given  $G = (V, E, w)$  and  $s, t \in V$ , find the  $s-t$  cut with the minimum value.

- Solve the max-flow problem with  $\forall (u, v) \in E: c(u, v) = w(u, v)$
- Let  $f$  be the maximum flow and construct  $G'$
- $L$ : vertices reachable from  $s$  in  $G'$
- $R = V \setminus L$
- Return  $\{L, R\}$

### Integrality Theorem.

• **Theorem.** If each  $c(e)$  is an integer, then the value of the maximum flow  $f$  is an integer.

• **Understanding.** If each  $c(e)$  is an integer, there exists a flow  $f$  to maximize the total flow value, such that each edge's flow is an integer.

### Edmonds-Karp Algorithm

Implement FordFulkerson with BFS

### Algorithm 12: Edmonds-Karp Algorithm

EdmondsKarp( $G = (V, E)$ ,  $s, t, c$ ):

initialize  $f$  such that  $\forall e \in E: f(e) = 0$ ; initialize  $G_f \leftarrow G$ ;

while there is an  $s-t$  path on  $G_f$ :

- find such a path  $p$  by BFS;
- find an edge  $e \in p$  with minimum capacity  $b$ ;
- update  $f$  that pushes  $b$  units of flow along  $p$ ;
- update  $G_f$ ;

endwhile

return  $f$

### Time

节点的 distance 根据 BFS 有不减，只需证明严格增

The distance of  $u$  from  $s$  increases by 2 between two critical.  $\text{dist}^{i+1}(u) = \text{dist}^i(v) + 1 \geq \text{dist}^i(v) + 1 \geq \text{dist}^i(u) + 2$

The max distance is  $V$ , so each edge can only be critical for  $V$  times, at least 1 edge become critical in one iteration, so the number of iteration is  $O(|V||E|)$ , each iteration takes  $O(E)$ , so the complexity is  $O(VE^2)$

### Dinic's Algorithm

Build a level graph:

- Vertices at Level  $i$  are at distance  $i$ .
- Only edges go from a level to the next level are kept.
- Can be done in  $O(E)$  time using a similar idea to BFS.

Blocking flow: push flow on multiple s-t paths, each s-t path must contain a critical edge.

Initialize  $f$  to be the empty flow and  $G^f = G$ .

Iteratively do the followings until  $\text{dist } t = \infty$ :

- Construct the level graph  $G_L^f$  for  $G^f$
- find a blocking flow on  $G_L^f$
- update  $f$  and  $G^f$

### Finding a blocking flow:

Iteratively do the followings, until no path from  $s$  to  $t$ :

- Run a forward DFS.
- Two possibilities:
  - End up at  $t$ : in this case, we update  $f$  (by pushing flow along the path) and remove the critical edge
  - End up at a dead-end, a vertex  $v$  with no out-going edges in  $G_L^f$ : in this case, we remove all the incoming edges of  $v$

### Time

At least one edge is removed after each search. Total number of searches:  $O(E)$  while Each search takes at most  $|V|$  steps.

Time complexity for each iteration  $O(V \cdot E)$ .

After one iteration, a new edge  $(u, v)$  appearing in  $G^{f+1}$  (but not in  $G^f$ ) must be "backward":  $\text{dist}^i(u) = \text{dist}^i(v) + 1$ .

We again have that  $\text{dist}(u)$  is non-decreasing

### Iteration Times

Proving  $\text{dist}^{i+1}(t) > \text{dist}^i(t)$ :

- Consider an arbitrary  $s-t$  path  $p$  in  $G_L^{f+1}$  with length  $\text{dist}^{i+1}(t)$ .
- We have  $\text{dist}^{i+1}(t) \geq \text{dist}^i(t)$  by monotonicity.
- Suppose for the sake of contradiction that  $\text{dist}^{i+1}(t) = \text{dist}^i(t)$ .
- Case 1: all edges in  $p$  also appear in  $G_L^i$ .
  - Then  $p$  is a shortest path containing no critical edges in  $G_L^i$ .
  - Contracting to the definition of blocking flow!

Proving  $\text{dist}^{i+1}(t) > \text{dist}^i(t)$ :

- Case 2:  $p$  contains an edge  $(u, v)$  that is not in  $G_L^i$ .
  - If  $(u, v)$  was not in  $G_L^i$ , then  $(v, u)$  was critical in the last iteration. We have  $\text{dist}^i(u) = \text{dist}^i(v) + 1$ .
  - If  $(u, v)$  was in  $G^i$  but not  $G_L^i$ , by the definition of level graph, we have  $\text{dist}^i(u) \geq \text{dist}^i(v)$ .
  - In both cases above,  $\text{dist}^i(u) \geq \text{dist}^i(v)$ .
  - We have  $\text{dist}^{i+1}(u) \geq \text{dist}^i(u)$  by monotonicity,
  - and we have  $\text{dist}^{i+1}(v) \geq \text{dist}^i(v, t)$

So we have  $\text{dist}^{i+1}(t) \geq \text{dist}^i(t) + 1$ . Besides,  $\text{dist}(t)$  maximum is  $|V|$  or  $\infty$  so the total number of the iteration is at most  $V$

So the time complexity is  $O(V^2 E)$

### Application

A graph is regular if all the vertices have the same degree.

A matching is perfect if all the vertices are matched.

A regular bipartite graph always has a perfect matching.

### Hall's Marriage Theorem

The matching problem on a bipartite graph  $G = (A, B, E)$ .

For a subset  $S \subseteq A$ , let  $N(S) \subseteq B$  be the set of vertices that are incident to vertices in  $S$ .

**Hall's Marriage Theorem** There exists a matching of size  $|A|$  if and only if  $S \leq |N(S)|$  for every  $S \subseteq A$ .

**proof** Given  $\forall S: S \leq |N(S)|$ , suppose the maximum matching has size  $M < |A|$ . 分情况讨论切割在哪 If  $L_A, L_B, R_A, R_B \neq \emptyset$   $M = |L_B| + |R_A|, |L_A| + |R_A| = |A|, M < |A|$  so  $L_A > L_B$

If there exist an edge from  $L_A$  to  $L_B$ , the cut is  $\infty$

Thus,  $N(L_A) \leq L_B < L_A$  contradiction

**By setting the capacity to 1, the Dinic's algorithm runs in  $O(E\sqrt{V})$**

Because the search takes  $O(1)$ , and search at most  $O(E)$  times.

1. If the iteration ends in  $\sqrt{V}$ , we have finished
2. Else: let  $f$  be the flow after  $\sqrt{V}$  iterations

In each iteration, for each  $v \in V \setminus \{s, t\}$ , either its in-degree is 1, or its out-degree is 1.

**Integrality Theorem:** there exists a maximum integral flow  $f'$  in  $G'$ .

$f'$  consists of vertex-disjoint paths with flow 1 (from flow conservation)

So each path length  $\geq \sqrt{V}$ ,  $\frac{V}{\sqrt{V}} = \sqrt{V}$ ,  $v(f') \leq \sqrt{V}$

## Linear Programming

基础的解决方式就是通过不断换元，把所有东西取到系数小于0 范围大于0。

Vertex is A point at the intersection of  $n$  linearly independent hyperplanes.

Edge is the intersection of  $n - 1$  linearly independent hyperplanes.

Move from one vertex to another adjacent vertex along an edge:

- Relax one of the  $n$  constraint and impose another.
- The new vertex can be computed by solving a system of  $n$  linear equations.

For Variable with unrestricted signs, introduce two variables  $x_+$  and  $x_-$  with standard constraints  $x_+, x_- \geq 0$  and Replace  $x$  with  $x_+ - x_-$

A linear program can be solved in a polynomial time.

## Linear Program (LP)

- Standard Form LP:

$$\max(\vec{c})^T \vec{x}$$

$$\text{subject to } A\vec{x} \leq \vec{b}$$

$$\vec{x} \geq 0$$

## LP Relaxation

Integer Programming is NP-complete, even for the zero-one special case. We can use the fact that LP is polynomial-time solvable to design approximation algorithm. Then “round” the fractional solution to integral one.

## LP duality

### Strong Duality Theorem

- **Theorem [Strong Duality Theorem].** Let  $\mathbf{x}^*$  be the optimal solution to (a) and  $\mathbf{y}^*$  be the optimal solution to (b), then  $\mathbf{c}^T \mathbf{x}^* = \mathbf{b}^T \mathbf{y}^*$ .

$$\begin{array}{ll} \text{maximize } \mathbf{c}^T \mathbf{x} & \text{minimize } \mathbf{b}^T \mathbf{y} \\ \text{subject to } A\mathbf{x} \leq \mathbf{b} & \text{subject to } A^T \mathbf{y} \geq \mathbf{c} \\ \mathbf{x} \geq 0 & \mathbf{y} \geq 0 \end{array} \quad \begin{array}{l} (\text{a}) \\ (\text{b}) \end{array}$$

Primal feasible      Primal OPT = Dual OPT      Dual feasible

## Formulation as Linear Program

- The **maximum flow problem** can be formulated by a linear program.

$$\begin{array}{ll} \text{maximize } \sum_{w:(s,u) \in E} f_{su} & \\ \text{subject to } 0 \leq f_{uv} \leq c_{uv}, & \forall (u, v) \in E \\ \sum_{v:(v,u) \in E} f_{vu} = \sum_{w:(v,w) \in E} f_{uw} & \forall u \in V \setminus \{s, t\} \end{array}$$

- Ford-Fulkerson Method implements the simplex method.

## We also make it easier

$$\begin{array}{ll} \text{maximize } \sum_{w:(s,u) \in E} f_{su} & \\ \text{subject to } f_{uv} \leq c_{uv}, & \forall (u, v) \in E \rightarrow y_{uv} \\ \sum_{v:(v,u) \in E} f_{vu} - \sum_{w:(v,w) \in E} f_{uw} = 0 & \forall u \in V \setminus \{s, t\} \rightarrow z_u \\ f_{ub} \geq 0 & \forall (u, v) \in E \end{array}$$

## Compute Its Dual Program

$$\begin{array}{ll} \text{minimize } \sum_{(u,v) \in E} c_{uv} y_{uv} & \\ \text{subject to } y_{su} + z_u \geq 1 & \forall u: (s, u) \in E \\ y_{vt} - z_v \geq 0 & \forall v: (v, t) \in E \\ y_{uv} - z_u + z_v \geq 0 & \forall (u, v) \in E, u \neq s, v \neq t \\ y_{uv} \geq 0 & \forall (u, v) \in E \end{array}$$

- We aim to show the LP above describes the min-cut problem.

- Let  $\text{OPT}_{\text{dual}}$  be its optimal objective value. We need to show  $\text{OPT}_{\text{dual}}$  is the size of the min-cut.

## Some Intuitions

$$\begin{array}{ll} \text{minimize } \sum_{(u,v) \in E} c_{uv} y_{uv} & \\ \text{subject to } y_{su} + z_u \geq 1 & \forall u: (s, u) \in E \\ y_{vt} - z_v \geq 0 & \forall v: (v, t) \in E \\ y_{uv} - z_u + z_v \geq 0 & \forall (u, v) \in E, u \neq s, v \neq t \\ y_{uv} \geq 0 & \forall (u, v) \in E \end{array}$$

- $y_{uv}$  describes if edge  $(u, v)$  is cut:  $y_{uv} = \begin{cases} 1 & \text{if } (u, v) \text{ is cut} \\ 0 & \text{otherwise} \end{cases}$
- $z_u$  describes u's "side":  $z_u = \begin{cases} 1 & \text{if } u \text{ is on the } s-\text{side} \\ 0 & \text{if } u \text{ is on the } t-\text{side} \end{cases}$

## Totally Unimodular Matrix

- **Definition.** A matrix  $A$  is **totally unimodular** if every square submatrix has determinant 0, 1 or -1.

- **Theorem.** If  $A \in \mathbb{R}^{m \times n}$  is totally unimodular and  $\mathbf{b}$  is an integer vector, then the polytope  $P = \{\mathbf{x}: Ax \leq \mathbf{b}\}$  has integer vertices.

### A Proof Sketch.

- If  $\mathbf{v} \in \mathbb{R}^n$  is a vertex of  $P$ , Then there exists an invertible square submatrix  $A'$  of  $A$  such that  $A'\mathbf{v} = \mathbf{b}'$  for some sub-vector  $\mathbf{b}'$  of  $\mathbf{b}$ .
- By Cramer's Rule, we have  $v_i = \frac{\det(A'_i|\mathbf{b}')}{\det(A'_i)}$ , where  $(A'_i|\mathbf{b}')$  is the matrix with  $i$ -th column replaced by  $\mathbf{b}'$ .
- $\det(A'_i) = \pm 1$  and  $\det(A'_i|\mathbf{b}') \in \mathbb{Z}$ . Thus,  $\mathbf{v}$  is integral.

## Corollary on Integrality of LP

- **Theorem.** If  $A \in \mathbb{R}^{m \times n}$  is totally unimodular and  $\mathbf{b}$  is an integer vector, then the polytope  $P = \{\mathbf{x}: Ax \leq \mathbf{b}\}$  has integer vertices.

- Since there always exists optimum at a vertex of the feasible region of LP, we have the following corollary.

- **Corollary.** If  $A$  is unimodular, then the optimal solution to LP (a) is integral when  $\mathbf{b}$  is integral, and the optimal solution to LP (b) is integral when  $\mathbf{c}$  is integral.

$$\begin{array}{ll} \text{maximize } \mathbf{c}^T \mathbf{x} & \text{minimize } \mathbf{b}^T \mathbf{y} \\ \text{subject to } A\mathbf{x} \leq \mathbf{b} & \text{subject to } A^T \mathbf{y} \geq \mathbf{c} \\ \mathbf{x} \geq 0 & \mathbf{y} \geq 0 \end{array} \quad \begin{array}{l} (\text{a}) \\ (\text{b}) \end{array}$$

## Proving $Z$ is totally unimodular by Induction...

- Base Step: Each cell of  $Z$  belongs to  $\{0, 1, -1\}$ .

- Inductive Step: Suppose every  $k \times k$  submatrix of  $Z$  has determinant belongs to  $\{0, 1, -1\}$ . Consider any  $(k+1) \times (k+1)$  submatrix  $Z'$ .

- Case 1: If a row of  $Z'$  is all-zero, then  $\det(Z') = 0$ .

- Case 2: If a row of  $Z'$  contains only one non-zero entry, then  $\det(Z')$  equals to  $\pm 1$  times the determinant of a  $k \times k$  submatrix.  $\det(Z') \in \{0, 1, -1\}$  by induction hypothesis.

- Case 3: If every row of  $Z'$  has two non-zero entries (one of them is -1 and the other is 1), then  $\det(Z') = 0$ :

- Adding all the column vectors, we get a zero vector.

A Framework for Proving Theorems Using Strong Duality □

Write down the primal and dual LPs. □ Justify that the

primal and dual LPs describe the corresponding problems. □

If the problem described is discrete, prove that the corresponding LP always gives integral solution. – Total Unimodularity □ Apply strong duality theorem.

## Minimax Theorem

- Suppose  $A$  chooses strategy first. Knowing that  $B$  will play the best response,  $A$  will choose an optimal strategy  $\mathbf{x}$  that maximizes his/her utility.

$B$  plays the best response given  $A$ 's strategy  $\mathbf{x}$ .

$$\max_{\mathbf{x}} \min_{\mathbf{y}} \sum_{i,j} G_{i,j} x_i y_j$$

Given  $B$  plays the best response,  $A$  choose a strategy maximizing the utility.

- Suppose  $B$  chooses strategy first. Similarly, the utility for  $A$  is

$$\min_{\mathbf{y}} \max_{\mathbf{x}} \sum_{i,j} G_{i,j} x_i y_j$$

## Minimax Theorem

- **Minimax Theorem:**

$$\max_{\mathbf{x}} \min_{\mathbf{y}} \sum_{i,j} G_{i,j} x_i y_j = \min_{\mathbf{y}} \max_{\mathbf{x}} \sum_{i,j} G_{i,j} x_i y_j$$

- Who chooses strategy first doesn't matter!

## P, NP, NP-Completeness

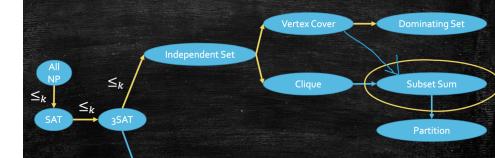
- P A decision problem  $f: \Sigma^* \rightarrow \{0, 1\}$  is in P, if there exists a polynomial time TM  $\mathcal{A}$  such that  $\neg \mathcal{A}$  accepts  $x$  if  $f(x) = 0$  –  $\mathcal{A}$  rejects  $x$  if  $f(x) = 1$

contains path,k-flow,prime

- Some famous NP-hard problems

- SAT
- Vertex Cover
- Independent Set
- Subset Sum
- Hamiltonian Path
- partition: divide a set to two sum-equal set
- SAT  $\leftrightarrow$  3-SAT

## Our Reduction Graph



- SAT  $\rightarrow$  3SAT

- $(l_1 \vee l_2 \vee \dots \vee l_k) = (l_1 \vee l_2 \vee y_1) \wedge (\neg y_1 \vee l_3 \vee y_2) \wedge \dots \wedge (\neg y_{k-2} \vee l_{k-1} \vee l_k)$

- 3SAT  $\rightarrow$  Independent Set

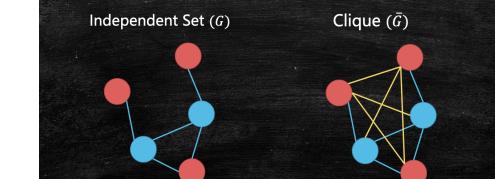
$$\begin{array}{l} \phi = (x_1 \vee x_3 \vee \neg x_4) \wedge (x_2 \vee \neg x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_2 \vee x_3) \\ G: \begin{array}{c} x_1 \\ x_3 \\ \cdot \\ \neg x_4 \\ x_2 \end{array} \end{array} \quad k = 3$$

- Independent Set  $\rightarrow$  Vertex Cover

- Choose the vertexes which are not chosen in independent set.

- Independent Set  $\rightarrow$  Clique

- $S$  is an Indeindent Set in  $G$  if and only if  $S$  is a clique in  $\bar{G}$ .



- Vertex Cover  $\rightarrow$  Dominating Set

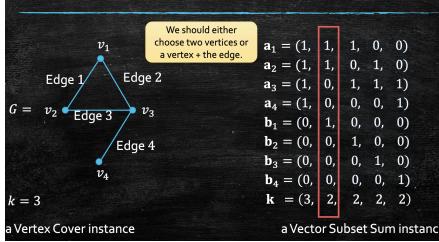
- a dominating set is a subset of vertexes  $S$  such that, for any  $v \in V \setminus S$ , there is a vertex  $u \in S$  that is adjacent to  $v$ .

- let all vertexes connected to each other and add new vertexes to each edge.

- Vertex Cover  $\rightarrow$  Subset Sum

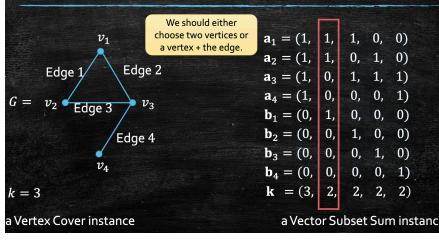
- Vertex Cover  $\leq_k$  VectorSubsetSum\*

### Example



•  $\text{VectorSubsetSum}^* \leq_k \text{SubsetSum}$

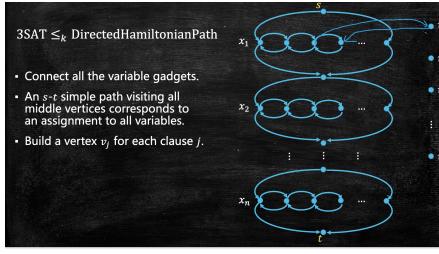
### Example



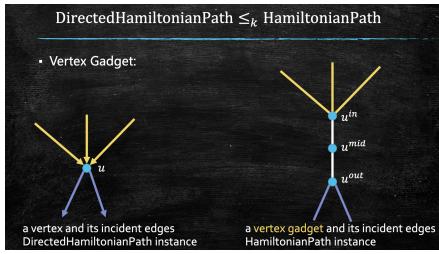
把向量看成 10 进制数

• 3SAT  $\longrightarrow$  Hamiltonian Path

•  $3SAT \leq_k$  有向图中的哈密顿路



• 有向图哈密顿路  $\leq_k$  哈密顿路



• 子图同构解决团， $G'=G$ ， $H'$  is a complete graph with  $k$  vertices

• 将顶点覆盖问题归约到集合覆盖问题。具体步骤如下：

• 给定一个顶点覆盖问题的实例  $(G=(V,E),k)$ 。构造一个新的集合覆盖问题实例

•  $(U,S,k)$ ，其中： $U$  是包含  $|E|$  个元素的集合，每个元素对应于  $G$  中的一条边。 $S$  是包含  $|V|$  个子集的集合，每个子集对应于  $G$  中的一个顶点  $v$ ，子集  $S_v$  包含所有与顶点  $v$  相连的边。 $k' = k$

• 无嫉妒分配问题将价值设为相等的可以解决 partition

• 背包问题的判断形式，可以将价值和大小设为  $k$  来解决 subsetnum 问题

三着色问题：使用 T (true) F (false) N (neutral)

构建  $tfn$  的三角形和  $tf$ ,  $fn$ ,  $nt$  成一个三角形，分配不同的颜色，对于一个命题，创建  $x$  和  $\neg x$  并相连并连接到  $n$ ，确保有一个对有一个错。对于一个括号，创建命题  $m$  并连接到  $n$ ,  $f$  确保选  $t$ ,

