

Mathematical Optimization (linear programming)

$$x \in \mathbb{R}^n; c \in \mathbb{R}^n; A \in \mathbb{R}^{n \times m}; b \in \mathbb{R}^m$$

• canonical form LP: $\max c^T x$ subj.to: $Ax \leq b$ and $x \geq 0$

general LP can be reconstructed with:

neg. x constr.: $x_i \leq 0 \rightarrow$ substit x_i with $x_i = -x_i'$	minimization: $\min c^T x \rightarrow \max -c^T x$
no x constr.: $x_i \in \mathbb{R} \rightarrow$ substit x_i with $x_i = x_i^+ - x_i^-$	lower bound: $A_i x \geq b_i \rightarrow -A_i x \leq -b_i$
	equality: $A_i x = b_i \rightarrow A_i x \geq b_i; -A_i x \geq -b_i$

• standard form LP: $\max c^T x$ subj.to: $Ax = b$ and $x \geq 0$

canonical LP from standard LP: $A_i x \leq b_i \rightarrow y_i + A_i x = b_i; y_i \geq 0$ y_i : slack variables appended to x

example: $x_1 + 4x_2 \leq 40$
 $2x_1 + x_2 \leq 42$
 $1.5x_1 + 3x_2 \leq 36$

$$\Rightarrow \begin{array}{cccc|c} y_1 & y_2 & y_3 & x_1 & x_2 & \\ \hline 1 & 0 & 0 & 1 & 4 & 40 \\ 0 & 1 & 0 & 2 & 1 & 42 \\ 0 & 0 & 1 & 1.5 & 3 & 36 \end{array}$$

$B = (1, 2, 3) \leftarrow A$ b

allowed operations (keep same solution)

- change row order
- multiply row with non-zero number
- add multiple of one row to another

• basis: $B = (\beta(1), \dots, \beta(m))$; $\beta(i) \in \{1, \dots, n+m\}, i=1, \dots, m$ ($\beta(i)$: column # of A where column = e_i)

• basis exchange:
 modify A, b to change basis
 without changing solution

$$\begin{array}{cccc|c} 1 & 0 & 0 & 1 & 4 & 40 \\ 0 & 1 & 0 & 2 & 1 & 42 \\ 0 & 0 & 1 & 1.5 & 3 & 36 \end{array} \Rightarrow \begin{array}{l} \textcircled{1} = \frac{1}{4} \textcircled{1} \\ \textcircled{2} = \textcircled{2} - \frac{1}{4} \textcircled{1} \\ \textcircled{3} = \textcircled{3} - \frac{3}{4} \textcircled{1} \end{array} \Rightarrow \begin{array}{cccc|c} \frac{1}{4} & 0 & 0 & \frac{1}{4} & 1 & 10 \\ -\frac{1}{4} & 1 & 0 & \frac{7}{4} & 0 & 32 \\ -\frac{3}{4} & 0 & 1 & \frac{3}{4} & 0 & 6 \end{array}$$

$\hookrightarrow B = (1, 2, 3) \Rightarrow$ exchange $i=1, k=5 \Rightarrow \hookrightarrow B = (5, 2, 3)$

• basic solution:
 set non-basic var. to 0

$$\begin{array}{cccc|c} \frac{1}{4} & 0 & 0 & \frac{1}{4} & 1 & 10 \\ -\frac{1}{4} & 1 & 0 & \frac{7}{4} & 0 & 32 \\ -\frac{3}{4} & 0 & 1 & \frac{3}{4} & 0 & 6 \end{array} \Rightarrow \begin{array}{l} x_2 = 10 - \frac{1}{4}y_1 - \frac{1}{4}x_1 \\ y_2 = 32 + \frac{1}{4}y_1 - \frac{7}{4}x_1 \\ y_3 = 6 + \frac{3}{4}y_1 - \frac{3}{4}x_1 \end{array} \Rightarrow \begin{array}{l} y_1^* = 0, x_1^* = 0 \\ x_2^* = 10, y_2^* = 32, y_3^* = 6 \end{array}$$

• basic feasible solution:

basic solution that is also feasible \Leftrightarrow all $x^*, y^* \geq 0$

• short tableau:
 (= compact notation)

$$\begin{array}{ccccc} i \rightarrow & 2 & 3 & 1 & \\ k \rightarrow & 1 & 2 & 3 & 4 & 5 \\ & y_1 & y_2 & y_3 & x_1 & x_2 \\ \hline & \frac{1}{4} & 0 & 0 & \frac{1}{4} & 1 & 10 \\ & -\frac{1}{4} & 1 & 0 & \frac{7}{4} & 0 & 32 \\ & -\frac{3}{4} & 0 & 1 & \frac{3}{4} & 0 & 6 \end{array} \Rightarrow \begin{array}{ccccc} i = & k = & \rightarrow & 1 & 4 \\ & \downarrow & \downarrow & & \\ & y_1 & x_1 & & \\ \hline 1 & 5 & x_2 & \frac{1}{4} & \frac{1}{4} & 10 \\ 2 & 2 & y_2 & -\frac{1}{4} & \frac{7}{4} & 32 \\ 3 & 3 & y_3 & -\frac{3}{4} & \frac{3}{4} & 6 \end{array}$$

basic solution x_2^*, y_2^*, y_3^* for $x_1^* = 0, y_1^* = 0$

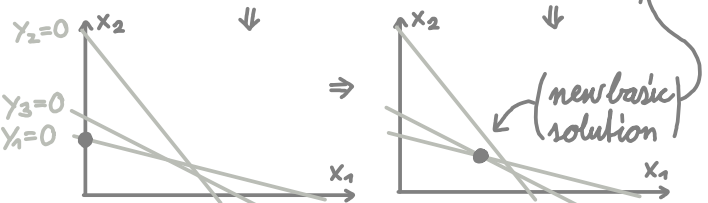
\hookrightarrow basis exchange formula:

$$\begin{array}{l} a_{ik}' = \frac{1}{a_{ik}} \text{ (pivot)} \\ a_{jk}' = -\frac{a_{jk}}{a_{ik}} \text{ (pivot col.)} \\ a_{il}' = \frac{a_{il}}{a_{ik}} \text{ (pivot row)} \end{array} \quad \dots \quad \begin{array}{l} a_{jl}' = a_{jl} - \frac{a_{jk} a_{il}}{a_{ik}} \\ b_j' = \frac{b_j}{a_{ik}} \\ b_j' = b_j - \frac{a_{jk} b_i}{a_{ik}} \end{array}$$

exchange

$i=3, k=4$:

$$\begin{array}{cccc|c} & y_1 & x_1 & & \\ \hline x_2 & \frac{1}{4} & \frac{1}{4} & & 10 \\ y_2 & -\frac{1}{4} & \frac{7}{4} & & 32 \\ y_3 & -\frac{3}{4} & \frac{3}{4} & & 6 \end{array} \Rightarrow \begin{array}{cccc|c} & y_1 & y_3 & & \\ \hline x_2 & \frac{1}{2} & -\frac{1}{3} & & 8 \\ y_2 & \frac{5}{4} & -\frac{7}{3} & & 18 \\ x_1 & -1 & \frac{4}{3} & & 8 \end{array}$$



cond. for feasible basic solution to stay feasible

- $a_{ik} > 0$ (pivot nonnegative)
- $b_j / a_{jk} \geq b_i / a_{ik} \forall j$ (quotient rule)

• short tableau with cost: append variable z to x to track objective of basic solution ($z = c^T x$)

$$\begin{array}{cccc|c} z & y_1 & \dots & y_m & x_1 & \dots & x_n \\ 1 & 0 & \dots & 0 & -c_1 & \dots & -c_n \\ 0 & \text{I} & & & \text{A} & & \\ & \text{L} & & & \text{J} & & \end{array} \Rightarrow \begin{array}{cccc|c} z & x_1 & \dots & x_n \\ & -c_1 & \dots & -c_n \\ y_1 & a_{11} & \dots & a_{1n} \\ \vdots & \vdots & & \vdots \\ y_m & a_{m1} & \dots & a_{mn} \end{array} \begin{array}{c} b_1 \\ \vdots \\ b_m \end{array}$$

cond. for increasing objective after exchange: $a_{ok} < 0$

(basis exchange formula same for objective row as for other rows.)

simplex method

- 1) start with a feasible tableau $\Leftrightarrow b_1, \dots, b_m \geq 0$
- 2) perform exchange step with a pivot a_{ik} that satisfies:
 - $a_{ik} > 0$ and $b_j/a_{jk} \geq b_i/a_{ik} \forall j \rightarrow$ will remain feasible
 - $a_{ok} < 0 \rightarrow$ will increase objective
- 3) repeat ② until:
 - $a_{ok} > 0 \forall k \rightarrow$ basic solution is optimal solution!
 - $\exists k$ s.t. $a_{ok} < 0$ & $a_{ik} \leq 0 \forall i \rightarrow$ solution is unbounded!

multiple pivots could satisfy these cond.
 additional rules that improve efficiency:

- pick column with most negative a_{ok}
- pick viable column with smallest index k
 \hookrightarrow "Blade's rule": guaranteed to terminate

• finding a feasible basic solution (for when initial tableau is unfeasible)

original problem: $\max C^T x$ subj.to: $y + Ax = b$ and $x \geq 0, y \geq 0$

auxiliary problem: $\max -x_0$ subj.to: $y + Ax - (1, \dots, 1)^T \cdot x_0 = b$ and $x \geq 0, y \geq 0, x_0 \geq 0$

\rightarrow problem always feasible (with large x_0)! if $x_0^* = 0$, then x^*, y^* feasible solutions of original problem!

$$\begin{array}{cccc|c} & x_1 & \dots & x_n & x_0 \\ z & 0 & \dots & 0 & 1 & 0 \\ y_1 & a_{11} & \dots & a_{1n} & -1 & b_1 \\ \vdots & \vdots & & \vdots & \vdots & \vdots \\ y_m & a_{m1} & \dots & a_{mn} & -1 & b_m \end{array}$$

pivot on column x_0 and
 row with most negative b_i
 \hookrightarrow guaranteed feasible sol.

use above simplex method to find x_0^*, x^*, y^*

- $x_0^* > 0$: original problem is infeasible
- $x_0^* = 0$: use x^*, y^* as feasible starting point to solve original problem!

dual problem

\hookrightarrow canonical form!

primal problem: $\max C^T x$ subj.to: $Ax \leq b, x \geq 0 \rightarrow$ dual problem: $\min b^T y$ subj.to: $A^T y \geq c, y \geq 0$

$$\left[\begin{array}{l} \max 4x_1 + x_2 + 5x_3 + 3x_4 \\ \text{s.t.: } x_1 - x_2 - x_3 + 3x_4 \leq 1 \\ 5x_1 + x_2 + 3x_3 + 8x_4 \leq 55 \\ -x_1 + 2x_2 + 3x_3 - 5x_4 \leq 3 \\ x_1, x_2, x_3, x_4 \geq 0 \end{array} \rightarrow \begin{array}{l} \text{find linear comb. of constr.} \\ \text{s.t. every } x \text{ coeff. dominates} \\ \text{its coeff. in } C^T \text{ and resulting} \\ \text{constraint is minimal} \end{array} \right. \left. \begin{array}{l} 4x_1 + x_2 + 5x_3 + 3x_4 = C^T x \\ \begin{pmatrix} x_1 - x_2 - x_3 + 3x_4 \leq 1 \\ 5x_1 + x_2 + 3x_3 + 8x_4 \leq 55 \\ -x_1 + 2x_2 + 3x_3 - 5x_4 \leq 3 \end{pmatrix} \cdot \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} \end{array} \rightarrow \begin{array}{l} \min y_1 + 55y_2 + 3y_3 \\ \text{s.t.: } y_1 + 5y_2 - y_3 \geq 4 \\ -y_1 + y_2 + 2y_3 \geq 1 \\ -y_1 + 3y_2 + 3y_3 \geq 5 \\ -3y_1 + 8y_2 - 5y_3 \geq 3 \\ y_1, y_2, y_3 \geq 0 \end{array} \right]$$

• rel. to standard LP: primal slack var. $x^s \hat{=} y$ dual optim. var. $\left(\max C^T x \text{ subj.to: } x^s + Ax = b ; x^s, x \geq 0 \right)$
 dual slack var. $y^s \hat{=} x$ primal optim. var. $\left(\max -b^T y \text{ subj.to: } y^s - A^T y = -c ; y^s, y \geq 0 \right)$

• weak duality theorem: $z = C^T x \leq b^T y = w$ feasible x objective \leq feasible y objective

• strong duality theorem: $z^* = C^T x^* = b^T y^* = w^*$ optimum of primal = optimum of dual

(usefull e.g. if some non-optimal z, w are found that are close \rightarrow can stop, since optimum is between)

p \ d	OPT	INF	UNB
OPT	✓	✗	✗
INF	✗	✓	✓
UNB	✗	✓	✗

• complementary slackness theorem: necessary and sufficient cond. for x^* and y^*
 $(A)_i x^* = b_i$ OR $y_i^* = 0 \quad \forall i=1, \dots, m$ AND $(A^T)_j y^* = c_j$ OR $x_j^* = 0 \quad \forall j=1, \dots, n$ (usefull to compute x^* if y^* is known and the opposite)

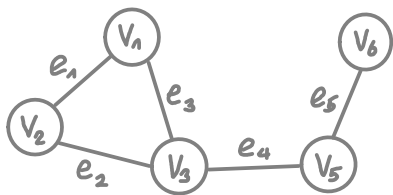
• sensitivity theorem: for relaxed constr. $Ax \leq b + t$ (t : small!) $\rightarrow z_{\text{new}}^* = z^* + t^T y^*$

\hookrightarrow if $y_i = 0$: constr. i is inactive \rightarrow relaxing it with $t_i > 0$ won't raise objective

\hookrightarrow if $y_i > 0$: relaxing constr. i with $t_i > 0$ will raise objective. larger $y_i \rightarrow$ larger increase in z^*

combinatorial optimization

undirected, unweighted graph:



vertices: $V = \{V_1 \dots V_n\}$
edges: $E = \{e_1 \dots e_m\}$
graph: $G = (V, E)$

edge representation in memory:

- adjacency matrix

	V_1	V_2	V_3	V_4	V_5
V_1	0	1	1	0	0
V_2	1	0	1	0	0
V_3	1	1	0	0	1
V_4	0	0	0	0	1
V_5	0	0	1	1	0

- incidence list:

V_1 :	e_1	e_3	
V_2 :	e_1	e_2	
V_3 :	e_2	e_3	e_4
V_4 :	e_5		
V_5 :	e_4	e_5	

- Breadth-First search (for shortest path): find smallest # of edges connecting v_1 to $u \in V := d(v_1, u)$

$$\bar{d}(v_1, u) = \begin{cases} 0 & u = v_1 \\ \infty & u \neq v_1 \end{cases} ; k=1 ; L = \{v_1\}$$

while $L \neq \emptyset$ do:

$L_{\text{new}} = \emptyset$

for all $u \in N(L) = \{u \in V \mid \exists w \in L, \{u, w\} \in E\}$ do:

if $\bar{d}(v_1, u) = \infty$ then $\bar{d}(v_1, u) = k$, $L_{\text{new}} \leftarrow u$

$k \leftarrow k+1$, $L \leftarrow L_{\text{new}}$

proof: show $D_k = \bar{D}_k$ by induction $\left(\begin{array}{l} D_k = \{u \in V \mid d(v_1, u) = k\} \\ \bar{D}_k = \{u \in V \mid \bar{d}(v_1, u) = k\} \end{array} \right)$

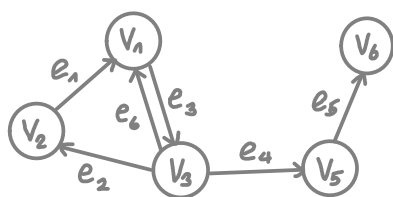
$$D_0 = \{v_1\} = \bar{D}_0 \quad \checkmark$$

assume $D_r = \bar{D}_r \forall r \leq k$, prove $D_{k+1} = \bar{D}_{k+1}$:

$\bar{D}_{k+1} \subseteq D_{k+1}$: let $u \in \bar{D}_{k+1}$. since $u \in N(D_k) \rightarrow d(v_1, u) \leq k+1$
and with $d(v_1, u) > k \rightarrow d(v_1, u) = k+1 \rightarrow \bar{D}_{k+1} \subseteq D_{k+1}$

$D_{k+1} \subseteq \bar{D}_{k+1}$: let $u \in D_{k+1} \rightarrow \exists \text{ path } (v_1, \dots, w, u) \rightarrow w \in D_k$
 $\rightarrow u \in N(D_k) \rightarrow u \in \bar{D}_{k+1} \rightarrow D_{k+1} \subseteq \bar{D}_{k+1}$ ■

directed, positive weighted graph:



graph: $G = (V, E)$
vertices: $V = \{V_1 \dots V_n\}$
edges: $E = \{e_1 \dots e_m\}$
weights: $l: E \rightarrow \mathbb{Z}_{>0}$

path: $P = \{e_a, e_b, \dots\}$ path length: $l(P) = \sum_{e \in P} l(e)$

shortest path: $d(s, v) = \min_P l(P)$ s.t. P is $s-v$ path

comments:

- if path $l(s \rightsquigarrow w \rightsquigarrow t) = d(s, t)$ then $l(s \rightsquigarrow w) = d(s, w)$
- all edges used by shortest paths form a tree

- Dijkstra's algorithm (for shortest path):

$$M = \{s\}, d_v = \infty \forall v \in V \setminus \{s\}, d_s = 0$$

while $M \neq V$:

$$u = \underset{v \in V \setminus M}{\text{argmin}} d_v$$

$$M \leftarrow M \cup \{u\}$$

for all $e = (u, w) \in \delta_+(u)$, $w \in V \setminus M$:


if $d_w > d_u + l(e)$ then $d_w \leftarrow d_u + l(e)$

proof: show $d_v = d(s, v) \forall v \in V$ by induction

at iter. 1: $d_s = d(s, s) = 0 \quad \checkmark$

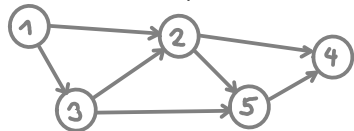
assume at iter. i : $d_x = d(s, x) \forall x \in M \rightarrow$ show at $i+1$: $d_u = d(s, u)$

$d_u < d(s, u)$: can't happen, as d_u always some path or ∞

$d_u > d(s, u)$:  $d_y = l(P_y) \leq l(P) = d(s, u) < d_u \quad \nexists$ ■

- longest path problem: can be built by flipping all weights to negative and searching shortest path.
problem is that subpath of longest path is itself not longest. Dijkstra's alg. breaks... very hard problem!

special case for directed acyclic graphs DAG:

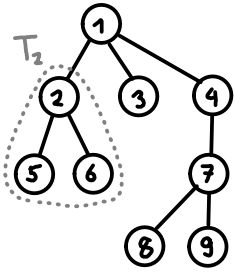


vertices sorted, so all edges point right.

in this case a subpath of the longest path is also the longest subpath!

• **trees**: any 2 vertices are connected by exactly one path.

- **independent set problem**: largest set of vertices that don't share edges $S \subseteq V$ s.t. $\forall u, v \in S: \{u, v\} \notin E$



T : entire tree with root at v_1

T_i : subtree with root at v_i

X_i : size of max. indep. set in T_i

Y_i : " , without using v_i

Z_i : " , with using v_i

comments:

• if $v_i \notin S$ then $|S \cap V[T_i]| = X_i \quad \forall v_j$ children of v_i

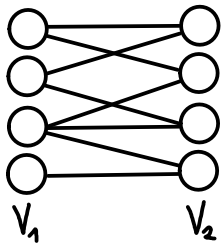
• if $v_i \in S$ then $|S \cap V[T_i]| = Y_i \quad \forall v_j$ children of v_i

algorithm: traverse tree bottom up, updating Y_i, Z_i for each node:

$$Y_i = \sum_j \max(Y_j, Z_j) ; Z_i = 1 + \sum_j Y_j \text{ with } j \text{ children of } i \rightarrow |S| = X_1 = \max(Y_1, Z_1)$$

combinatorial optimization via LP

• **perfect bipartite matching problem**: find largest set $M \subseteq E$ s.t. $\forall e_1 \neq e_2, e_1, e_2 \in M: e_1 \cap e_2 = \emptyset$



$$G = (V_1 \cup V_2, E)$$

$$|V_1| = |V_2| = n$$

variable: $\forall e \in E \quad x_e \in \{0, 1\}$ (1 for pick e for matching M)

constraint: $\forall v \in V \quad \sum_{e \in \delta(v)} x_e = 1$ (perfect matching: one edge out of every vertex)

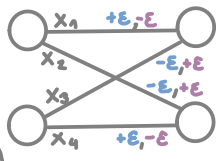
objective: $\max \sum_{e \in E} x_e \cdot c_e$ (c_e : cost of edge)

$$\rightarrow Z_{IP}^* = \max \sum_{e \in E} x_e \cdot c_e \text{ subj. to: } \sum_{e \in \delta(v)} x_e = 1 \quad \forall v \in V ; x_e \geq 0 \quad \forall e \in E ; x_e \in \mathbb{Z}$$

$$\text{relaxed: } Z_{LP}^* = \max \sum_{e \in E} x_e \cdot c_e \text{ subj. to: } \sum_{e \in \delta(v)} x_e = 1 \quad \forall v \in V ; x_e \geq 0 \quad \forall e \in E ; x_e \in \mathbb{R}$$

in this problem if x^* is any extreme point (basic feasible solution) of the relaxed problem, then $x^* \in \mathbb{Z}$.
since LP solutions are always extreme points it follows that $Z_{IP}^* = Z_{LP}^*$!

(proof by contradiction: assume x extreme point and fractional



for x to be fractional and feasible it has to contain loops of even length. two new feasible solutions y, z can be built by adding/subtracting a sufficiently small ϵ to edges of x as shown.

(b.c. $0 < x_e \leq 1 \quad \forall e$ for fractional x) $\rightarrow x = \frac{1}{2}y + \frac{1}{2}z \rightarrow x$ is not an extreme point!

• **maximum matching / minimum vertex cover**:

max. matching: $Z_{IP}^* = \max \sum_{e \in E} x_e \text{ subj. to: } \sum_{e \in \delta(v)} x_e \leq 1 \quad \forall v \in V, x_e \geq 0 \quad \forall e \in E, x_e \in \mathbb{Z}$

relaxed max. matching: $Z_{LP}^* = \max \sum_{e \in E} x_e \text{ subj. to: } \sum_{e \in \delta(v)} x_e \leq 1 \quad \forall v \in V, x_e \geq 0 \quad \forall e \in E, x_e \in \mathbb{R}$

relaxed min vertex cover: $W_{LP}^* = \min \sum_{v \in V} y_v \text{ subj. to: } y_v + y_u \geq 1 \quad \forall \{u, v\} \in E, y_v \geq 0 \quad \forall v \in V, y_v \in \mathbb{R}$ } dual!

min vertex cover: $W_{IP}^* = \min \sum_{v \in V} y_v \text{ subj. to: } y_v + y_u \geq 1 \quad \forall \{u, v\} \in E, y_v \geq 0 \quad \forall v \in V, y_v \in \mathbb{Z}$

$\rightarrow Z_{IP}^* \leq Z_{LP}^* = W_{LP}^* \leq W_{IP}^* \rightarrow$ weak duality holds for max. matching \Leftrightarrow min. vertex cover!

for bipartite graphs these can be shown to be equalities (similar to above proof)