

Problem-Sheet 4

My Solution

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Task 1:

a)

Given: Undirected Graph $G = (E, V)$.

Unfortunaltely, I did not know how to generate optimization problems in latex. Hence I decided to write these froms by hand and just take a picture.

From the following given primal LP

$$\begin{array}{ll} \text{Maximize} & -cx \\ \text{s. t.} & x(A) \leq |V| - \mathcal{K}(A) \quad \forall \quad A \subset E \\ & x(E) = |V| - 1 \\ & x_e \geq 0 \quad \forall \quad e \in E \end{array}$$

Fig: Given initial primal LP

We want to find the corresponding dual LP.

As a first step I slightly reformulate the given Problem:

$$\begin{aligned}
 & \max \quad -\vec{c}_e^T \vec{x}_e \\
 & \text{s.t.} \quad \sum_{e \in A} x_e \leq |V| - \chi(A), \quad \forall A \subseteq E \\
 & \quad \quad \sum_{e \in E} x_e = |V| - 1 \\
 & \quad \quad x_e \geq 0, \quad \forall e \in E
 \end{aligned}$$

Fig: Reformulated primal LP

Note that I simply used the definition of $x(A)$ which is equal to $X(A) = \sum_{e \in A} x_e$ for any subset A of E .

The respective dual LP is then:

$$\min \sum_{A \in E} \underbrace{(|V| - \mathcal{K}(A))}_{=: b_A} \gamma_A$$

$$\text{s.t.} \quad \sum_{A \in E} \gamma_A \geq -c_e, \quad \forall e \in E$$

$$\gamma_A \geq 0, \quad \forall A \in E$$

$$\gamma_E \equiv \text{free}$$

Fig: Dual version

b)

Given an undirected Graph $G = (E, V)$ as shown in figure 1. E denotes the set of its edges, V denotes the set of its vertices.

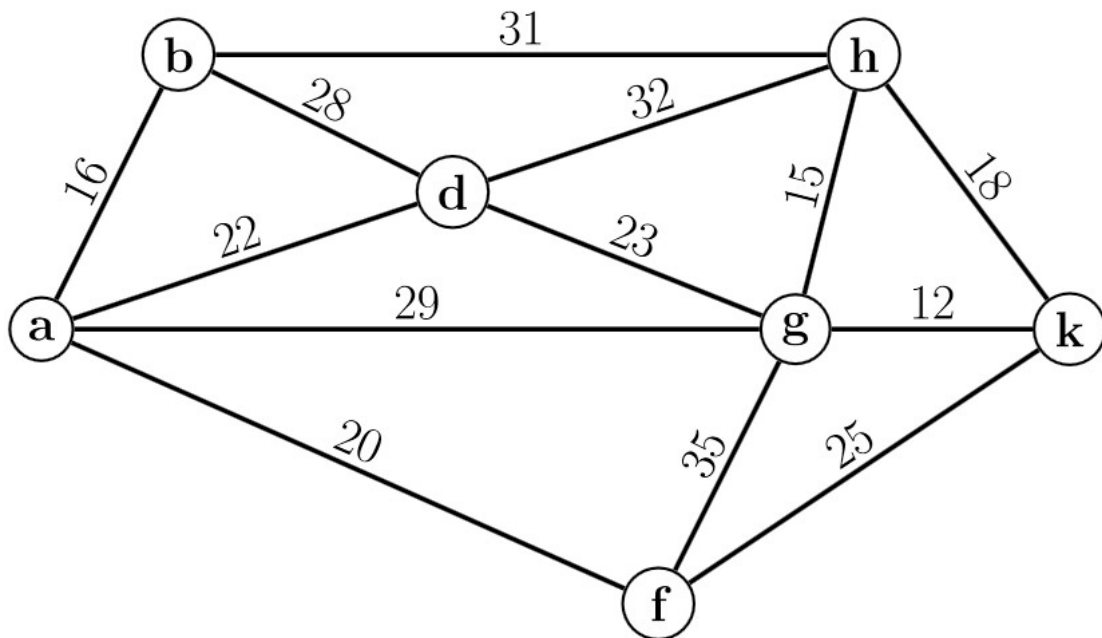


Figure 1: Given Graph $G = (E, V)$ to solve.

Using the Kruskal Algorithm I get the following MSP from the graph in figure 1:

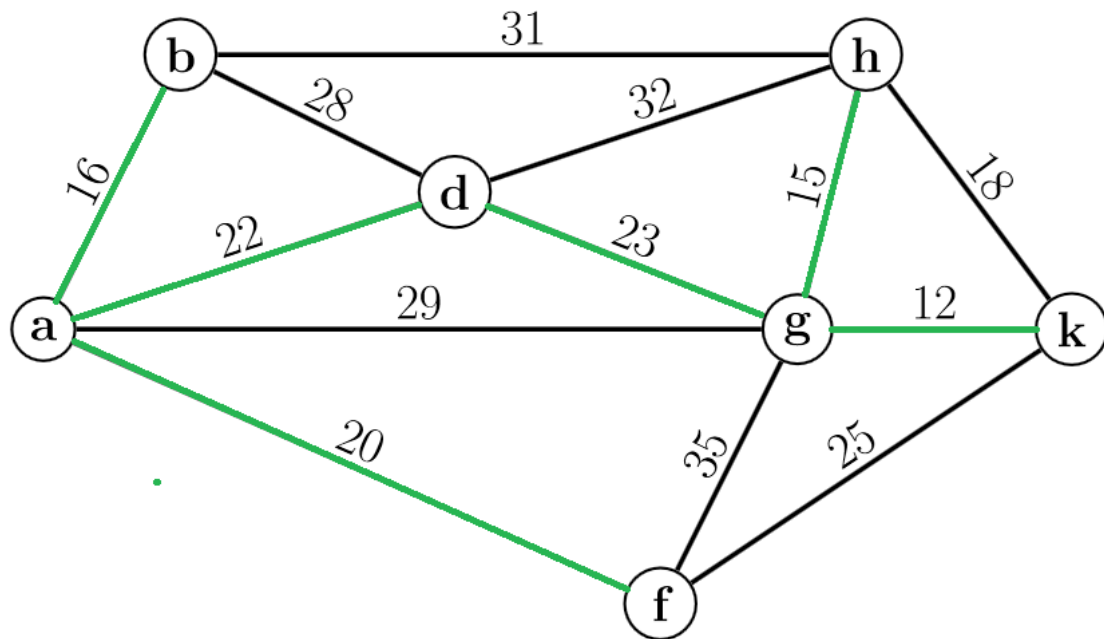


Figure 2: Minimal Spanning Tree of given graph (in green)

Next let us sort all the edges in the set E of the given graph G in an ascending order according to their edge weights. The following table lists all the sorted edges. Note that the first row contains the edge with the lowest weight, whereas the last edge contains the edge with the highest weight:

Edge e	Weight e_c	Edge e taken x_e
gk	12	1
gh	15	1
ab	16	1
hk	18	0
af	20	1
ad	22	1
dg	23	1
fk	25	0
bd	28	0
ag	29	0
bh	31	0
dh	32	0
fg	35	0

In addition there is a 3rd row telling us whether we have taken this edge for our MST (equal 1) or we

have not taken it (equal zero). Note that I use the following notation: an edge ab denotes an edge that connects the vertex a with the vertex b .

The total cost of this MST from figure 2 is then equal to the dot product of the vector $\mathbf{e_c}$ and $\mathbf{x_e}$, i.e. **$\text{dot}(\mathbf{e_c}, \mathbf{x_e}) = 108$**

this product is the optimal solution for the primal LP – using the vectors

- the vector $\mathbf{e_c}$ which corresponds to \mathbf{c} in the primal LP.
- The vector $\mathbf{x_e}$ which corresponds to $\mathbf{x^0}$ in the primal LP.

Some important facts:

- Note that E is the set of all edges in G , ordered ascending according to the edge weights and
- R_i denotes the subset of E which is equal to $R_i = (e_1, \dots, e_i)$ for all $i=1, \dots, m$.
- We use the dual LP (linear program) from task a)

In the following a table which contains the solution vectors of the dual problem LP:

Index I	R_i	$K(A)$	$b = V - K(A)$	y^0_A
1	R_1	6	1	3
2	R_2	5	2	1
3	R_3	4	3	2
4	R_4	4	3	2
5	R_5	3	4	2
6	R_6	2	5	1
7	R_7	1	6	2
8	R_8	1	6	3
9	R_9	1	6	1
10	R_{10}	1	6	2
11	R_{11}	1	6	1
12	R_{12}	1	6	3
13	R_{13}	1	6	-35

According to the given definition:

$$y_A^0 = \begin{cases} c_{e_{i+1}} - c_{e_i} & \text{for } A = R_i, \quad i = 1, \dots, m-1 \\ -c_{e_m} & \text{for } A = R_m, \\ 0 & \text{for all other } A \subset E \end{cases}$$

Eq 1: Equation in order to compute y_A^0

I computed the values of y_A^0 by using Eq.1 and applying it to all R_i sets:

In practice I ordered all edge-costs ascending:

D		3		1		2		2		2		1		2		3		1		2		1		3	
C	12		15		16		18		20		22		23		25		28		29		31		32		35
I	1		2		3		4		5		6		7		8		9		10		11		12		13

Here the row C denotes all the sorted costs

I denotes the index of the i-th element in in the sorted edge-costs collection.

Row D denotes the differences between the (i+1)-th cost and the (i-th) cost.

This gives us m-1, i.e. 12 values for y_A^0 the last value is -35 since for $A = R_m$ y_A^0 is equal to $-c_{e_m}$. This is the explanation how I computed the vector y_A^0 in the table from above.

Thus, the solution to the dual LP is equal to the dot product between the vectors y_A^0 and \mathbf{b} (from above's table) times (-1) – please see the dual LP from task a). This is written out equal to $\text{dot}(y_A^0, \mathbf{b}) = 108$.

Last let us perform some sanity check – how reliable are our found solutions:

Def(Strong Duality Theorem): IF there exists a primal and a dual feasible solution, then there exists a primal feasible solution x and a dual feasible solution y such that $cx = yb$. The solutions x and y are then optimal.

Thus, we simple can check whether $cx = yb$ holds true for our case:

since $\text{dot}(y_A^0, \mathbf{b}) = 108 = \text{dot}(\mathbf{e}_c, \mathbf{x}_e)$

Our solutions to the primal and dual LP are optimal.

c)

Check the complementary slackness condition for two positive primal and two dual variables.

Def(complementary slackness condition): A primal feasible solution x and a dual feasible solution y are optimal, if and only if (i) and (ii) hold true:

(i) $y_i > 0$ and y_i non-neg variable $\Rightarrow \sum_{j=1}^n a_{ij}x_j = b_i$

(ii) $x_j > 0$ and x_j non-neg. Variable $\Rightarrow \sum_{i=1}^m a_{ij}y_i = c_j$

Unfortunately I was not able to find an easy example using this graph.

d)

for the primal LP: we are looking for an vector x and c (take edge k and cost of edge k for the k -th element of these vectors).

For the dual LP :we are looking for an vector b and y .

The primal LP has many inequalities but just some unknowns whereat the dual LP has many parameter but just the number of edges constraints.

e)

Primal LP

The image shows a handwritten primal linear programming problem on a piece of paper. The problem is written in blue ink. It starts with a maximization objective function: $\max - \begin{pmatrix} 10 \\ 15 \\ 20 \\ 30 \end{pmatrix}^T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix}$. Below this, the constraints are listed under "s.t": $x_{v_1 v_3} \leq 1$, $x_{v_1 v_4} \leq 1$, $x_{v_1 v_2} \leq 1$, and an equality constraint $x_{v_1 v_2} + x_{v_1 v_3} + x_{v_1 v_4} = 3$. The variables x_1, x_2, x_3, x_4 are used in the objective function, while the constraints use edge notation $x_{v_i v_j}$.

Figure Primal explicit form:

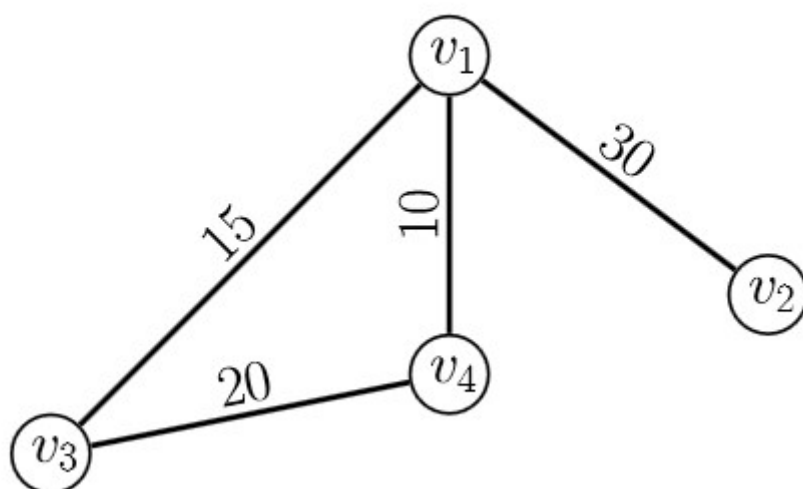
Note that I used the following variable mapping:

$x_1 := x_{v_1 v_4}$; $x_2 := x_{v_1 v_3}$; $x_3 := x_{v_3 v_4}$; $x_4 := x_{v_1 v_2}$

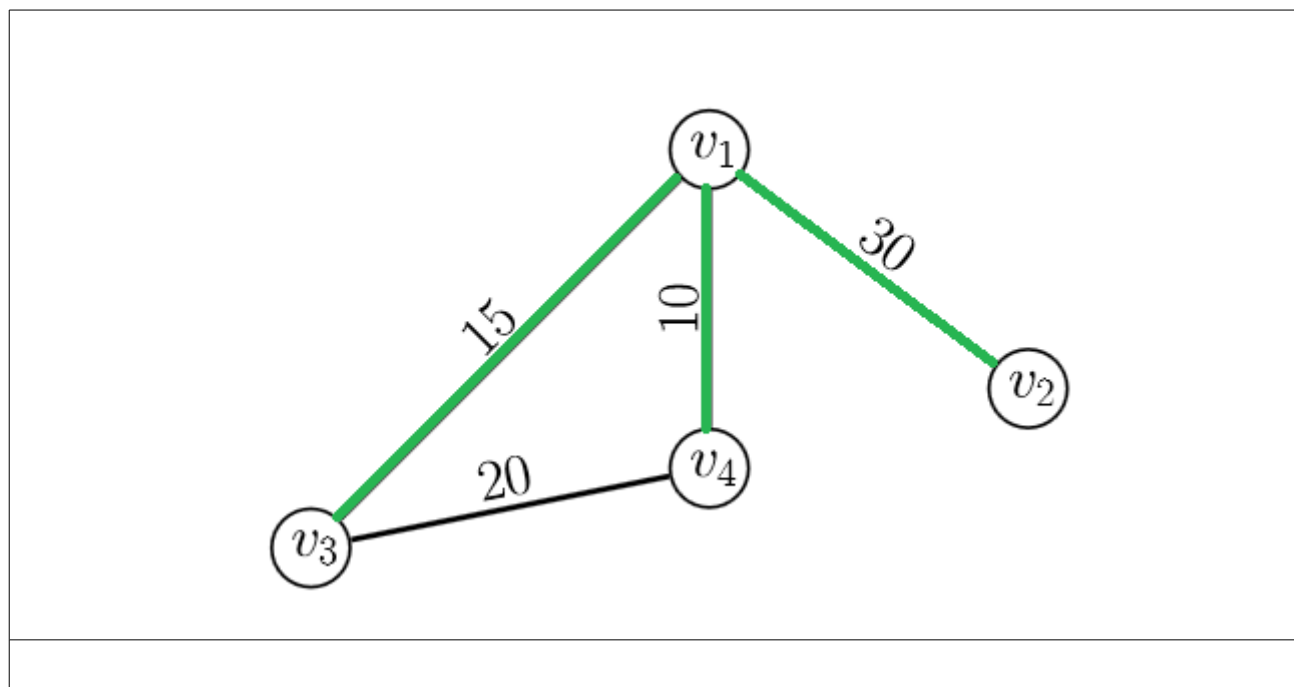
$$\begin{array}{ll} \min & \gamma_1 + 2\gamma_2 + 2\gamma_3 + 3\gamma_4 \\ \text{s.t.} & \gamma_1 \leq 10 \\ & \gamma_1 + \gamma_2 \leq 15 \\ & \gamma_1 + \gamma_2 + \gamma_3 \leq 20 \\ & \gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 \leq 30 \end{array}$$

f)

Given: undirected graph $G = (V, E)$



Which has the following mst:



by applying the same approach I used in the previous part, i find the vectors x and c for the primal LP and y and b for the dual LP. I gain use the formula from Eq. 1 in order to compute y :

Sorted edges according to their weights (in ascending order):

$c_e =: c$	e	$x_e =: x$
10	v_1v_4	1
15	v_1v_3	1
20	v_3v_4	0
30	v_1v_2	1

c_e denotes the cost of edge e

e is an edge, where v_1v_2 is the edge connecting vertex v_1 with vertex v_2 .

x_e tells us whether we take this edge into our mst

$_b = V - K(A)$	$K(A)$	I	y
1	3	1	5
2	2	2	5
2	2	3	10
3	1	4	-30

We can check the validity of our solution by again using the Strong duality theorem.

If $cx = yb$ holds true, then, our solution is indeed optimal.

Since $cx = 55 = yb$ we have shown that we have found an optimal solution.