

# Group assignment 2

## Advanced Algorithms and Data Structures

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### CLRS 29.1-5

Bring the following Linear programming problem into slack form:

$$\begin{array}{llllll} \text{Maximize} & 2x_1 & & -6x_3 & & \\ \text{Subject to} & x_1 & +x_2 & -x_3 & \leq & 7 \\ & 3x_1 & -x_2 & & \geq & 8 \\ & -x_1 & +2x_2 & +2x_3 & \geq & 0 \\ & & & x_1, x_2, x_3 & \geq & 0 \end{array}$$

First step is to bring the problem to standard form by multiplying the the second and third constraint with  $-1$ . This gives:

$$\begin{array}{llllll} \text{Maximize} & 2x_1 & & -6x_3 & & \\ \text{Subject to} & x_1 & +x_2 & -x_3 & \leq & 7 \\ & -3x_1 & x_2 & & \leq & -8 \\ & x_1 & -2x_2 & -2x_3 & \leq & 0 \\ & & & x_1, x_2, x_3 & \geq & 0 \end{array}$$

To bring the standard form of this problem into slack form, the slack variables  $x_4, x_5, x_6 \geq 0$  are introduced and the terms are rearranged such that the slack variables are on the LHS of the equalities. This gives the following slack form:

$$\begin{array}{rclcl}
z = & & 2x_1 & & -6x_3 \\
x_4 = & 7 & -x_1 & -x_2 & +x_3 \\
x_5 = & -8 & +3x_1 & -x_2 & \\
x_6 = & & -x_1 & +2x_2 & +2x_3
\end{array}$$

The basic variables are the variables on the LHS,  $x_4, x_5, x_6$ , and the non-basic variables are the variables on the RHS,  $x_1, x_2, x_3$ .

## CLRS 29.2-6

The maximum-bipartite-matching problem can be expressed as a maximum flow problem as suggested in section 26.3 by defining the corresponding flow network  $G' = (V', E')$  for the bipartite graph  $G$ .

Consider the case where  $V = L \cup R$  is the vertex partition of  $G$  such that  $L$  and  $R$  are disjoint and all edges in  $E$  go between  $L$  and  $R$ . Let the source  $s$  and sink  $t$  be new vertices and define  $V' = V \cup \{s, t\}$ . The set of edges  $E'$  in the flow network are constructed by setting all edge capacities in  $E$  to one, and adding new directed edges of unit capacity from  $s$  to each vertex in  $L$  and from each vertex in  $R$  to  $t$ .

Much alike equations (29.47)-(29.50) in section 29.2, we can now write a linear program that given a bipartite graph  $G = (V, E)$  solves the maximum-bipartite-matching problem:

$$\begin{array}{ll}
\text{Maximize} & \sum_{v \in L} f_{sv} \\
\text{Subject to} & f_{uv} \leq 1 \quad \text{for each } u, v \in V, \\
& \sum_{v \in V} f_{vu} = \sum_{v \in V} f_{uv} \quad \text{for each } u \in V - \{s, t\}, \\
& f_{uv} \geq 0 \quad \text{for each } u, v \in V.
\end{array}$$

## CLRS 29.3-5

Solve the following linear program using **simplex**:

$$\begin{array}{llll}
\text{Maximize} & 18x_1 & + & 12.5x_2 \\
\text{Subject to} & x_1 & + & x_2 & \leq & 20 \\
& x_1 & & & \leq & 12 \\
& & & x_2 & \leq & 16 \\
& x_1, x_2 & & & \geq & 0
\end{array}$$

Writing the linear program in slack form, we obtain:

$$\begin{array}{rclcl}
 z & = & 0 & + & 18x_1 & + & 12.5x_2 \\
 x_3 & = & 20 & - & x_1 & - & x_2 \\
 x_4 & = & 12 & - & x_1 & & \\
 x_5 & = & 16 & & & - & x_2 \\
 x_1, x_2, x_3, x_4, x_5 & \geq & 0 & & & & 
 \end{array}$$

Initially, all nonbasic variables are set to zero such that we have  $x_3 = 20$ ,  $x_4 = 12$  and  $x_5 = 16$ . We start by investigating how much  $x_1$  can be increased without violating any constraints. Recognising that  $x_4$  is the binding constraint for  $x_1$ , it is apparent that  $x_1$  can be increased by 12. By pivoting we now obtain:

$$\begin{array}{rclcl}
 z & = & 216 & - & 18x_4 & + & 12.5x_2 \\
 x_3 & = & 8 & + & x_4 & - & x_2 \\
 x_1 & = & 12 & - & x_4 & & \\
 x_5 & = & 16 & & & - & x_2 \\
 x_1, x_2, x_3, x_4, x_5 & \geq & 0 & & & & 
 \end{array}$$

Next, we investigate by how much  $x_2$  can be increased. As  $x_3$  is the binding constraint, we can see that  $x_2$  can be increased by 8. Pivoting now results in:

$$\begin{array}{rclcl}
 z & = & 316 & - & 5.5x_4 & + & 12.5x_3 \\
 x_2 & = & 8 & + & x_4 & - & x_3 \\
 x_1 & = & 12 & - & x_4 & & \\
 x_5 & = & 8 & - & x_4 & + & x_3 \\
 x_1, x_2, x_3, x_4, x_5 & \geq & 0 & & & & 
 \end{array}$$

Since there are no more nonbasic variables in the objective function, the algorithm terminates. The solution we obtain is  $(12, 8, 0, 0, 8)$  with an objective value of 316.

## CLRS 29.4-1

Formulate the dual of the following (primal) linear programming problem:

$$\begin{array}{llll}
 \text{Maximize} & 18x_1 & +12.5x_2 & \\
 \text{Subject to} & x_1 & +x_2 & \leq 20 \\
 & x_1 & & \leq 12 \\
 & & +x_2 & \leq 16 \\
 & x_1, x_2 & & \geq 0
 \end{array}$$

The dual can be obtained by identifying the constants used in the primal, see equation 29.16-18 in CLRS, and inserting these into equation 29.83-85 in CLRS. This gives the following dual linear programming problem:

$$\begin{array}{llllll}
\text{Minimize} & 20y_1 & +12y_2 & +16y_3 & & \\
\text{Subject to} & y_1 & +y_2 & & \geq & 18 \\
& y_1 & & +y_3 & \geq & 12.5 \\
& & y_1, y_2, y_3 & \geq & 0 & 
\end{array}$$

### **RandQS – expected bound on $\mathbb{E}[d(i)]$**

Consider the proof for the number of comparisons performed by RandQS. In each iteration of the algorithm, the  $i$ 'th smallest element is compared to the  $j$ 'th smallest element as one of the two must be picked as a pivot. The conditional probability of picking  $i$  or  $j$  as pivot given that the pivot is picked uniformly at random in  $\{S_{(i)}, S_{(i+1)}, \dots, S_{(j)}\}$  is  $p_{ij} = \frac{2}{j-i+1}$ .

Suppose that the chosen pivot is  $j$ . Then we know that  $d(i) > d(j)$ , since  $i$  must be in a subtree of  $j$ . Thus, the expected depth of  $i$  is the expected number of ancestors. As we are only interested in the case where  $j$  is chosen as pivot, we have that  $\Pr[j \text{ is an ancestor of } i] = \frac{1}{j-i+1}$ . Thus, we can now find the expected depth:

$$\begin{aligned}
\mathbb{E}[d(i)] &= \sum_{j>i} \Pr[j \text{ is an ancestor of } i] \\
&= \sum_{j>i} \frac{1}{j-i+1} \\
&\leq \sum_{k=1}^{n-i+1} \frac{1}{k} \\
&\leq \sum_{k=1}^n \frac{1}{k} \\
&= H_n = O(\log n).
\end{aligned}$$

The last equality follows from Proposition B.4, as referred to in the randomized algorithms PDF.

## Randomized contraction – 99% certainty of a min-cut

As per the last paragraph of page 8 of the PDF, “*The probability of discovering a particular min-cut [...] is larger than  $2/n^2$* ”.

Let  $m$  be the number of runs of the randomized contraction min-cut algorithm needed to achieve 99% or higher certainty of finding a minimum cut.

Then  $m$  is the smallest integer satisfying the equation  $m \cdot \frac{2}{n^2} \geq 0.99$ :

$$\begin{aligned} m \cdot \frac{2}{n^2} &\geq 0.99 \\ \Leftrightarrow m &\geq 0.495n^2. \end{aligned}$$

Since  $m$  is an integer and the RHS of above inequality is not always integral, the value we are looking for is  $m = \lceil 0.495n^2 \rceil$ .

Example: if  $n = 4$ , then  $m = \lceil 7.92 \rceil = 8$  runs are required for 99% certainty of a min-cut, while for  $n = 100$ ,  $m = \lceil 4950 \rceil = 4950$  runs are required.

## Randomized algorithms PDF – exercise 1.2

### The general idea

We know that for any set  $S$  with  $|S| = n$ , there exist  $m = 2^{n-1} - 1$  distinct ways to partition  $S$  into two non-empty subsets.

Consider a connected graph  $G$  with  $|V| = n$ .  $V$  is a set of distinct vertices and can also be partitioned in  $m = 2^{n-1} - 1$  distinct ways.

The idea behind our solution is then this: Construct a graph  $G$  in such a way that the number of valid minimum cuts of  $G$  remain constant as  $n$  grows – if possible, then, since  $m = 2^{n-1} - 1$  grows exponentially with  $n$ , we will have constructed a graph in which the ratio of valid minimum cuts to the total number of candidate cuts decreases exponentially with  $n$ .

### Constructing the graph

Let  $G = (V, E)$  be an undirected graph, with  $V = \{v_0\} \cup V'$ , such that  $V'$  is a non-empty clique<sup>1</sup> of  $(n - 1) \geq 1$  vertices in  $G$ , and let  $E$ , the set of edges,

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<sup>1</sup>A subset of vertices in which every pair of two distinct vertices are adjacent.

consist of the set of edges in the clique  $V'$  as well as a single edge  $(v_0, v_i)$  for some vertex  $v_i \in V'$ . As such the size of  $V$  is:

$$\begin{aligned} |V| &= |V'| + |\{v_0\}| \\ &= (n-1) + 1 \\ &= n. \end{aligned}$$

Let  $(v_0, v_1)$  with  $v_1 \in V'$  be the single edge connecting the components  $V'$  and  $\{v_0\}$ . Then  $E$  is given by:

$$E = \{(u, v) \in V^2\} \cup \{(v_0, v_1)\}.$$

Figure fig. 1 shows an example graph for  $n = 5$ .

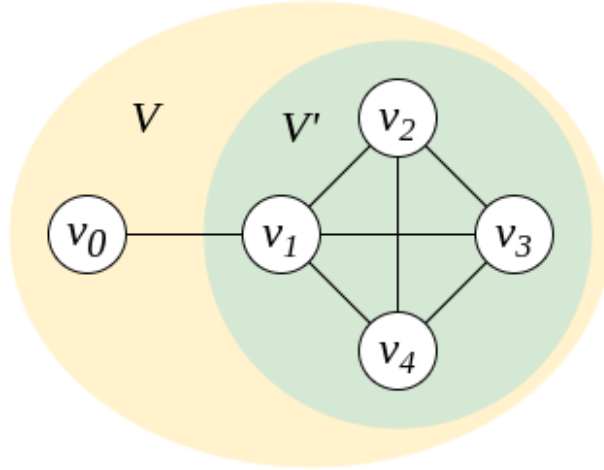


Figure 1: Example graph with  $|V| = n = 5$  and  $|V'| = 4$ .

Clearly, for any graph  $G$  constructed in this way, the minimum cut is unique and is given by  $C = (\{v_0\}, V')$ . The cut-set<sup>2</sup> is  $\{(v_0, v_1)\}$  and the value of the cut is always 1.

Since there are  $m = 2^{n-1} - 1$  possible partitionings and only 1 valid cut, the probability of the algorithm randomly generating this partitioning is:

$$\frac{1}{2^{n-1} - 1} = \frac{1}{O(2^n)} = O(2^{-n}).$$

<sup>2</sup>The set of edges with one endpoint in either subset of the partitioning.

## Randomized algorithms PDF – exercise 1.3

The pseudocode in fig. 2 shows how to obtain a Las Vegas algorithm from a Monte Carlo algorithm  $A$ . The function `to_las_vegas(A, pi)` takes as input a Monte Carlo algorithm  $A$  and a problem  $pi$  and repeatedly computes `solution = A(pi)` until a correct solution is produced. The pseudocode assumes an existing function `verify(pi, solution)` which, given a problem and a proposed solution, returns `True` if `solution` is a correct solution to the problem  $pi$ , and `False` otherwise.

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```
1 function to_las_vegas(A, pi) {  
2     do {  
3         solution = A(pi);  
4         success  = verify(pi, solution);  
5     } while not success;  
6  
7     return solution;  
8 }
```

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Figure 2: Obtaining a Las Vegas algorithm from Monte Carlo algorithm  $A$ .

First, the **do-while** loop in lines 2-5 repeatedly executes  $A(pi)$  until a correct solution is found. The loop can possibly run indefinitely, but since  $A$  has probability of success  $\gamma(n)$  and because the loop terminates immediately once a solution is verified as correct, we expect the loop to run for  $\lceil 1/\gamma(n) \rceil$  iterations on average.

Secondly, since  $A$  has expected run time  $O(T(n))$ , line 3 of the loop runs in expected time  $O(T(n))$ , and because we assume that we can verify the solution in time  $O(t(n))$ , line 4 of the loop runs in expected time  $O(t(n))$ . In total, a single iteration of the **do-while** loop takes expected time  $O(T(n) + t(n))$ . Since we expect the loop to run for  $\lceil 1/\gamma(n) \rceil$  iterations on average, the expected run time of the entire function is:

$$\begin{aligned} O\left(\left\lceil \frac{1}{\gamma(n)} \right\rceil \cdot (T(n) + t(n))\right) &= O\left(\frac{1}{\gamma(n)} \cdot (T(n) + t(n))\right) \\ &= O\left(\frac{T(n) + t(n)}{\gamma(n)}\right), \end{aligned}$$

which is what we wanted to show.

# Summaries

## psl788

### Linear Programming

- Short introduction
- Standard and slack form
- Simplex algorithm
- Proof of weak duality

### Randomized algorithms

- Random quicksort
  - Short explanation including an example
  - Proof of running time
- Las Vegas and Monte Carlo

## wlc376 – exam presentation dispositions

### Linear programming

1. intro:
2. standard vs slack form
3. give a small example of transforming a linear programming problem to standard, slack, and simplex form.
4. present SIMPLEX algorithm (and explain duality?)
5. prove weak duality

### Randomized algorithms

1. intro and motivation: algorithms with random choices; for some types of programs, randomized algorithms are simpler, faster, or both.
2. Las Vegas vs Monte Carlo algorithms (RandQS vs edge contraction min-cut)
3. present RandQS (and why it is a good example of a randomized algorithm)



4. prove  $O(n \log n)$  average case runtime of RandQS
5. if time: present edge contraction min-cut algorithm (??)

## **knx373**

### **Linear programming and optimization**

- Introduction to what a LP problem is. Keywords: Objective function, linear constraints, feasible solution/region, unbounded, optimal solution
- Standard and slack form
- Simplex algorithm
- Dual formulation of primal LP problem
- Weak duality including proof

### **Randomized algorithms**

- Motivation for using randomized algorithms
- Las Vegas (random quick sort) vs Monte Carlo algorithms (random min cut)
- Introduce random quick sort algorithm
- Proof of expected number of comparisons for RandQS
- If time: Converting algorithms (LV to MC and MC to LV)