Masters Dissertation

Approximation Algorithms for Stochastic Unsplittable Flow Problems

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To Dr. Indumati Karandikar,

Abstract

In this thesis, we present approximation algorithms for variants and special cases of the Stochastic Unsplittable Flow Problem (hereafter, sUFP). The objective of the sUFP is to optimally schedule tasks from a given set of tasks on an underlying graph, each of which is specified by a stochastic demand, a payoff and a pair of vertices between which it must be scheduled.Even very special cases of the sUFP, such as the sUFP on a single-edge graph with deterministic demands, are known to be NP-hard.

We present new polytime constant-factor approximation algorithms for the sUFP on Paths and Trees and for extensions where each task may correspond to more than two vertices. We consider two settings - a special-case in which all the capacities are equal and the general-case in which the capacities are arbitrary. In dealing with arbitrary capacities, we assume that the distribution underlying the demand for each task has maximum attainable value less than or equal to the least capacity among the edges in the graph, operating under what is known as the No Bottleneck Assumption.

Our approximation algorithms are obtained by combining approximations for instances in which all tasks are small and for those in which all tasks are large. They provide an approximation to a linear programming relaxation and hence may perform significatly better in practice than the guarantees we establish. These algorithms do not make decisions based on results of previously instantiated tasks, and are classified as non-adaptive algorithms, which leads to the result that the adaptivity gaps for these problems are bounded by a constant.

Contents

Chapter 1

Stochastic Unsplittable Flow Problems

1.1 Problem Specifications

In the Stochastic Unsplittable Flow Problem (hereafter, sUfpGeneral), we are given a graph $G = (V, E)$ and a set of tasks T. Let G have p vertices and m edges. Each edge $e \in E$ corresponds to a processor which can be used for at most c_e units of time. We call c_e the capacity of edge e. Each task $t \in T$ is specified by a pair of distinct vertices $\{a_t, b_t\} \in V$ and can be scheduled along any path between a_t and b_t. The size of the task t is given by a positive random variable S_t, whose distribution is given to the algorithm as input. [1] If task t is scheduled, we specify a path P_t for it. Task t then consumes S_t amounts of processing on each edge along path P_t. If we let $\widehat{c}_e$ be the residual capacity of edge e, the residual capacity of e becomes $\widehat{c}_e \leftarrow \max(0, \widehat{c}_e - S_t)$. A task is *successfully scheduled* if $S_t \leq \min_{e \in P_t} \widehat{c}_e$ and we get a payoff of v_t, else it is *unsuccessfully scheduled* and we get no payoff. Observe that even if the job is unsucessful, the capacity along all the edges in P_t is consumed to extent S_t or to complete consumption, whichever occurs first. The objective is to find a scheduling strategy to maximize the expected payoff.

Note that each task can be scheduled at most once. The random variable S_t is instantiated only when task t is scheduled and all scheduling decisions are irrevocable. Also note that since the sizes S_t of all tasks t are positive random variables, once an edge has zero residual capacity, it cannot be a part of any succesfully scheduled task.

We consider some special cases of sUfpGeneral based on restricting the graph:

- When the graph G is a tree, the problem is called the stochastic unsplittable flow problem on trees, or sUfpTree. In this case, we imagine the graph G as being rooted at some root node $r \in V$. The unique a_t-b_t path is now denoted by P_t. The *depth of node* v is the number of edges on the unique v-r path. The *depth of a path* is the depth of the least common ancestor (LCA) of the endpoints of the path. Equivalently, it is the depth of the least-depth node on the path. Assume that the tasks are numbered from $1, \ldots, n$ in non-decreasing order of depth, that for all tasks t, the terminals a_t and b_t are leaves in G, and that the root has a single child generality.

  If in an instance of sUfpTree, all edge capacities are equal, we get the *generalization of the Stochastic Resource Allocation Problem to a Tree* (hereafter, sRapTree). By scaling, we assume

[1] As will become apparent, we need to know only some statistics of this distribution for our algorithms.

for sRapTree that all processor capacities are 1.

- When the tree is a path, the problem is called sUfpPath. The vertices are numbered from 1 to $m+1$ along the path from left to right, and edges of the path from 1 to m. As in sUfpTree, the unique a_t-b_t path P_t consists of edges in the set $[a_t, b_t)$. We assume that the tasks are sorted by their left endpoints, i.e., $a_1 \leq \ldots \leq a_n$. Note that this is same as sorting the tasks by the depth of the corresponding path if we consider vertex 1 to be the root.

  If in an instance of sUfpPath, all edge capacities are equal, we get the *stochastic Resource Allocation Problem* (hereafter, sRapPath). By scaling, we assume for sRapPath, as we did for sRapTree that all processor capacities are 1.

We can also generalize the idea of scheduling pairs $\{a_t, b_t\}$ to scheduling sets of terminals. Specifically, when consdiering sUfpTree, we generalize our results as follows:

- A tree T' rooted at r' is called a *k-spider* if T' has at most k leaves, and the least common ancestor of any two nodes u, v in it is either the root r', or one of $\{u, v\}$. Equivalently, a k-spider is a set of k disjoint paths emanating from the root r'. Given a tree T, call a set $D_t \subseteq V$ a *k-spider set* if the subtree induced by these vertices is a k-spider set. Note that if $|D_t| \leq 2$, it is trivially a *2-spider set.* (An alternative definition is as follows: given D_t, let D_t' be a minimal subset which indices the same subtree as D_t. Then D_t' has the Helly-type condition that the lca of any pair of them is the same as the lca of the entire set.)

  The generalization of the sUfpTree where each task t corresponds to a k-spider set D_t, is called *sUfpTree with k-spiders* (hereafter, sUFPT-kS).

  Along similar lines, the generalization of the sRapTree where each task t corresponds to a k-spider set D_t, is called *sRapTree with k-spiders* (hereafter, sRAPT-kS).

  For sUFPT-kS and sRAPT-kS, let the spider induced by task t be denoted by P_t, and the tasks be numbered from $1, \ldots, n$ in non-decreasing order of the depth of the root of their corresponding spiders. As in the sUfpTree, we assume the terminals in each D_t are leaves and that the root has a single child.

- Finally, we also consider the generalization where G is a rooted tree and each task t corresponds to a subtree P_t of G. Our results will on the bound on the number of children of each node in G. We consider the case where all edge capacities are equal, and as before, scaled to 1. We refer to this problem as the *sRapPath on k-ary trees with subtrees* or sRAPkT-T. As in the sUfpTree, we assume that the tasks are numbered from $1, \ldots, n$ in non-decreasing order of the depth of the root of their corresponding subtrees.

Note that all problems mentioned here are special cases of *sUfpTree with edge subsets*, denoted hereafter by sUfpTreeEdgeSubset, which is the generalization of sUfpTree where each task corresponds to a unique subset of edges.

1.1.1 The No-Bottleneck Assumption

Improved results for unsplittable-flow problems have often been obtained under the *No-Bottleneck Assumption* (hereafter, NBA). In the stochastic context, the NBA says that for each task $t \in T$, the domain of the size random variable S_t is $(0, c_{\min}]$ where $c_{\min} = \min_{e \in E} c_e$. By scaling we assume that $c_{\min} = 1$, and hence the r.v.s $S_t \in (0, 1]$. We operate under the NBA for sUfpPath and sUFPT-kS.

1.2 Additional Notation

We denote the maximum capacity of any edge by $c_{\max} := \max_{e\in E} c_e$ and the maximum value in the support of the size of any job by $S_{\max} := \max_{t\in T} \max(S_t)$. Define $q_{\max} := \min\{c_{\max}, S_{\max}\}$. The *bottleneck capacity of task* t is defined as $b_t := \min\{c_e \mid e \in P_t\}$. The *truncated size* of task t is $\tilde{S}_t := \min\{S_t, b_t\}$ and its *mean truncated size* is $\mu_t := \mathbf{E}[\tilde{S}_t]$. The *effective payoff* of task t is defined as $\tilde{v}_t := v_t \cdot \Pr[S_t \le b_t]$. Note that under the NBA, $\tilde{S}_t = S_t$ and $\tilde{v}_t = v_t$ for all tasks t and that $q_{\max} = 1$ for all problems we will deal with in this paper.

If A denotes a set of tasks, then the set of tasks from A incident on processor e is defined as $A_e := \{t \in A \mid P_t \ni e\}$. We define the truncated size of A as $\mu(A) := \sum_{t\in A} \mu_t$.

1.3 Feasible Tasks and Non-Adaptive Algorithms

Since the sizes of the tasks are positive random variables it is not beneficial to schedule an yet-unscheduled task t if there exists a processor in P_t which is completely used up. We call such tasks infeasible, and the remaining yet-unscheduled tasks feasible at this time. For convenience of analysis, we adopt the convention that at a given point in time an algorithm can only schedule tasks feasible at that point in time.

The state at any point in time is completely defined by the residual capacities of all edges and the set of unscheduled tasks at that point in time. Each scheduling algorithm is completely specified by the feasible task it chooses to schedule for every state that may arise as a consequence of its previous decisions. Note that these choices may not be deterministic. Thus a scheduling algorithm provides a probability distribution over feasible tasks for each state that may arise as a consequence of its previous decisions.

Algorithms which make decisions based on the outcomes of previously scheduled tasks are referred to as *adaptive algorithms*. Those which premeditate a sequence of distinct tasks and schedule them sequentially, skipping only past the ones which become infeasible in the process are *non-adaptive algorithms*.

Let $\mathbb{A}$ denote the set of all scheduling algorithms for a given instance of sUfpTreeEdgeSubset. We denote by $\mathbb{A}_N$ the set of all non-adaptive scheduling algorithms for that instance of sUfpTreeEdgeSubset. Note that $\mathbb{A}_N \subseteq \mathbb{A}$. Let $\mathcal{P}(\mathcal{A})$ denote the random variable which equals the payoff of some scheduling algorithm $\mathcal{A} \in \mathbb{A}$. We define optimal payoff $OPT := \sup\{\mathbf{E}[\mathcal{P}(\mathcal{A})] | \mathcal{A} \in \mathbb{A}\}$ and non-adaptive optimal payoff $OPT_N := \sup\{\mathbf{E}[\mathcal{P}(\mathcal{A})] | \mathcal{A} \in \mathbb{A}_N\}$. The adaptivity gap for given problem is the supremum of OPT/OPT_N over all instances of that problem.

1.4 Contribution of this Paper

We give the first polynomial-time constant-factor approximation algorithms for the sRapPath, the sUfpPath under the NBA, the sUFPT-kS under the NBA and the sRAPT-kS. The last two results also imply, as a corollary, constant-factor approximation algorithms for the sUfpTree under the NBA and the sRapTree.

For the sRAPkT-T, we provide a polynomial-time non-adaptive approximation algorithm which achieves a constant-factor approximation to non-adaptive algorithms for sRAPkT-T. Whether this algorithm is a constant-factor approximation to any algorithm for sRAPkT-T is not known to us and is open to resolution.

All algorithms we present are non-adaptive and hence these results imply that the adaptivity gaps for the sRapPath, the sUfpPath under the NBA, the sUfpTree under the NBA and the sRapTree are all constant whereas those for the sUFPT-kS and the sRAPT-kS are polynomial in k.

1.5 Structure of Paper

In section 2 we define a linear program and show that an optimal solution to it is an upper bound on OPT. This result holds for sUfpTreeEdgeSubset and is essential to all approximation algorithms in this paper.

For each task $t \in T$, we say that task t is δ-small if $\mu_t \leq \delta b_t$ and δ-large if $\mu_t > \delta b_t$. For each special case of sUfpTreeEdgeSubset relevant to this paper we will give a polynomial-time non-adaptive constant-factor approximation algorithm for instances in which all tasks are δ-small and one for those instances in which all tasks are δ-large for some real δ. We will then combine these suitably to provide an algorithm which provides a polynomial-time non-adaptive constant-factor approximation for the problem in consideration.

In section 3 we provide the strategy for combining the constant-factor algorithms for the large tasks and small tasks special cases into a constant-factor approximation algorithm for the general case.

In section 4 we describe the approximation algorithms for instances of special cases of sUfpTreeEdgeSubset in which all tasks are small.

In section 5 we describe the approximation algorithms for instances of special cases of sUfpTreeEdgeSubset in which all tasks are large.

In section 6 we apply the results of sections 3, 4 and 5 to obtain the results that subsection 1.4 outlines.

Chapter 2

A Linear Programming Relaxation

As described in the previous section, the theme of this paper is polynomial-time algorithms, whose expected value is within a constant of the optimal solution to a linear program which is an upper bound for OPT. Since in many cases, OPT may itself be significantly smaller than the optimal solution to the linear program, the algorithms may provide significantly better approximations in practice than the constant factors that they guarantee.

This section establishes the LP relaxation which is central to all the results in this paper. The LP and its proof are straightforward extensions of the LP relaxation idea in The relaxation holds for sUfpTreeEdgeSubset, of which all problems we will consider in this paper are special cases.

Lemma 2.0.1 *Fix an algorithm $\mathcal{A}$, and let A denote the set of tasks scheduled by it. For processor $e \in E$, recall that A_e is the set of tasks from A incident on processor e. Then*

$$\mathbf{E}[\mu(A_e)] \leq c_e + q_{\max}$$

(As mentioned in §1.2, $q_{max} = 1$ for all problem settings that we consider in this paper.)

Proof. Let A^i denote the set of the first i tasks that $\mathcal{A}$ schedules. If $\mathcal{A}$ stops scheduling tasks after scheduling the $i'^{\text{ th}}$ task then for $i > i'$ we define $A^i = A^{i'}$. Note that

$$\mathbf{E}[\mu(A_e)] = \lim_{i \to \infty} \mathbf{E}[\mu(A_e^i)] = \sup_{i \geq 0} \mathbf{E}[\mu(A_e^i)]$$

Since $\tilde{S}_t \leq q_{\max}$ for all tasks t and since $\mathcal{A}$ cannot schedule any task which uses processor e after the size of scheduled tasks which use processor e equals or exceeds c_e we infer that

$$\sum_{t \in A_e^i} \tilde{S}_t \leq c_e + q_{\max}$$

Define $X_e^i = \sum_{t \in A_e^i} (\tilde{S}_t - \mu_t)$. Let us observe that $\mathbf{E}[X_e^{i+1} | X_e^i] = X_e^i$. If there are no more tasks which $\mathcal{A}$ schedules or if next task to be scheduled does not use processor e then this holds trivially. Otherwise, note that conditioned on the next task to be scheduled t_{next} we have $\mathbf{E}[X_e^{i+1} | X_e^i, t_{\text{next}}] = X_e^i + \mathbf{E}[\tilde{S}_{t_{\text{next}}}] - \mu_{t_{\text{next}}} = X_e^i$. Thus we can remove the conditioning to once again obtain $\mathbf{E}[X_e^{i+1} | X_e^i] = X_e^i$. We have now shown that the sequence X_e^i is a martingale and by the martingale property we conclude that $\mathbf{E}[X_e^i] = \mathbf{E}[X_e^0] = 0$. Linearity of expectation now gives us the result

$$\mathbf{E}[\mu(A_e^i)] = \mathbf{E}\big[\sum_{t \in A_e^i} \tilde{S}_t\big] \leq c_e + q_{\max}$$

This completes the proof of Lemma 2.0.1. ∎

2.1 The LP relaxations

For a vector $\mathbf{u} = (u_1, u_2, \ldots, u_m)$ of "capacities", the following LP is denoted by $\mathcal{L}(\mathbf{u})$:

$$\max \sum_{t \in T} \tilde{v}_t x_t$$

$$\text{subject to} \quad \sum_{t \in T_e} \mu_t x_t \le u_e \qquad \forall e \in E \qquad (L.1)$$

$$0 \le x_t \le 1 \qquad \forall t \in T \qquad (L.2)$$

Let $\phi(\mathbf{u})$ be the value of the optimal solution to $\mathcal{L}(\mathbf{u})$.

Another LP that will prove useful is $\mathcal{L}'(\mathbf{u})$:

$$\max \sum_{t \in T} \tilde{v}_t x_t \qquad (2.1.0.1)$$

$$\text{subject to} \quad \sum_{t \in T_e} x_t \le u_e \qquad \forall e \in E \qquad (L'.1)$$

$$0 \le x_t \le 1 \qquad \forall t \in T \qquad (L'.2)$$

Let $\phi'(\mathbf{u})$ denote the value of the optimal solution to $\mathcal{L}'(\mathbf{u})$.

Theorem 2.1.1 *The expected payoff of every scheduling algorithm for an instance of sUfpTreeEdgeSubset is bounded above by $\phi(\mathbf{c} + \mathbf{q}_{\max})$. Hence*

$$OPT \le \phi(\mathbf{c} + \mathbf{q}_{\max})$$

Proof. Consider a scheduling algorithm $\mathcal{A} \in \mathbb{A}$ and let A denote the set of tasks that it schedules. Let $\mathbf{x}$ denote the vector of size n whose t^{th} component $x_t = \Pr[t \in A]$. From this definition and from Lemma 2.0.1 we have that for all processors e

$$\sum_{t \in A_e} \mu_t x_t = \mathbf{E}[\mu(A_e)] \le c_e + q_{\max}$$

We infer that the x_t's satisfy the set of constraints (L.1). That they satisfy the set of constraints (L.2) follows trivially from their definition. Hence

$$\sum_{t \in T} \tilde{v}_t x_t \le \phi(\mathbf{c} + \mathbf{q}_{\max})$$

Let G_t denote the (random) indicator variable which indicates whether task t is successfully scheduled given that it was scheduled. Observe that $G_t = 1$ implies that $S_t \le b_t$. Hence

$$\begin{aligned}
\text{Expected profit due to task } t &= \mathbf{E}[v_t e_t | t \in A] \Pr[t \in A] \\
&= v_t \Pr[G_t = 1 | t \in A] \Pr[t \in A] \\
&\le v_t \Pr[S_t \le b_t] \Pr[t \in A] \\
&= \tilde{v}_t x_t
\end{aligned}$$

Hence $\mathcal{P}(\mathcal{A}) \le \sum_{t \in T} \tilde{v}_t x_t \le \phi(\mathbf{c} + \mathbf{q}_{\max})$ and since this is true for any $\mathcal{A} \in \mathbb{A}$ we conclude that $OPT \le \phi(\mathbf{c} + \mathbf{q}_{\max})$. ∎

Chapter 3

Combining Approximation Algorithms

The idea for combining algorithms in this section is an adaptation of the idea in ≪**Archit 3.0.0.1:** ref to Stoch Knapsack paper≫. **AK 3.0.0.1**

Theorem 3.0.2 *Consider an instance $\mathcal{I} = (G, T)$ of* sUfpTreeEdgeSubset *with optimal payoff OPT specified by the edge-capacitated graph G and the set of tasks T. Let T_1 and T_2 form a partition of T and consider instances $\mathcal{I}_1 = (G, T_1)$ and $\mathcal{I}_2 = (G, T_2)$ with optimal payoffs OPT_1 and OPT_2.*

If there exists, for instance $\mathcal{I}_1$, a polynomial-time non-adaptive algorithm $\mathcal{A}_1$, a polynomial-time computable quantity ξ_1 and a constant $\alpha_1 \geq 1$ such that,

$$\mathbf{E}[\mathcal{P}(\mathcal{A}_1)] \geq \xi_1 \geq \frac{1}{\alpha_1} OPT_1$$

and there exists, for instance $\mathcal{I}_2$, a polynomial-time non-adaptive algorithm $\mathcal{A}_2$, a polynomial-time computable quantity ξ_2 and a constant $\alpha_2 \geq 1$ such that,

$$\mathbf{E}[\mathcal{P}(\mathcal{A}_2)] \geq \xi_2 \geq \frac{1}{\alpha_2} OPT_2$$

then there exists, for instance $\mathcal{I}$ a polynomial-time non-adaptive algorithm $\mathcal{A}$ such that,

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{\alpha_1 + \alpha_2} OPT$$

Proof. Consider an optimal algorithm $\mathcal{A}_{OPT}$, for instance $\mathcal{I}$, which has expected payoff OPT. Now consider an algorithm $\mathcal{A}'_1$ for $\mathcal{I}_1$ which makes the same decisions as $\mathcal{I}$, instantiating but not scheduling the tasks in T_2 that $\mathcal{A}_{OPT}$ would have scheduled. Since the congestion at each edge because of the scheduling decisions of $\mathcal{A}'_1$ at each stage is atmost that of $\mathcal{A}_{OPT}$, we infer that the payoff of $\mathcal{A}'_1$ is at least the payoff of $\mathcal{A}_{OPT}$ due to tasks in T_1. Similarly there exists an algorithm $\mathcal{A}'_2$ for $\mathcal{I}_2$ whose payoff is at least the payoff of $\mathcal{A}_{OPT}$ due to tasks in T_2. We conclude that

$$\begin{aligned} OPT &\leq OPT_1 + OPT_2 \\ &\leq \alpha_1\xi_1 + \alpha_2\xi_2 \\ \max(\xi_1, \xi_2) &\geq \frac{OPT}{\alpha_1 + \alpha_2} \end{aligned}$$

The algorithm $\mathcal{A}$ does the following: It computes ξ_1 and ξ_2 in polynomial time. If ξ_1 is the greater of the two it executes $\mathcal{A}_1$ and ignores the tasks in T_2, otherwise it executes $\mathcal{A}_2$ and ignores the tasks in T_1. We conclude that

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \max(\xi_1, \xi_2) \geq \frac{1}{\alpha_1 + \alpha_2} OPT$$

We observe from the definition of $\mathcal{A}$ that it is a polynomial-time non-adaptive algorithm. This completes the proof of the claim. ∎

We will use Theorem 3.0.2 to obtain approximation algorithms for sRapPath, sUfpPath, sRAPT-kS and sUFPT-kS. To obtain an algorithm for sRAPkT-T which is a constant-factor approximation to non-adaptive algorithms, we need a slight variant of Theorem 3.0.2, stated below. Its proof is nearly identical and is not stated here so as to avoid repetition.

Theorem 3.0.3 *Consider an instance $\mathcal{I} = (G, T)$ of sUfpTreeEdgeSubset with non-adaptive optimal payoff OPT_N specified by the edge-capacitated graph G and the set of tasks T. Let T_1 and T_2 form a partition of T and consider instances $\mathcal{I}_1 = (G, T_1)$ and $\mathcal{I}_2 = (G, T_2)$ with non-adaptive optimal payoffs OPT_{N1} and OPT_{N2}.*

If there exists, for instance $\mathcal{I}_1$, a polynomial-time non-adaptive algorithm $\mathcal{A}_1$, a polynomial-time computable quantity ξ_1 and a constant $\alpha_1 \geq 1$ such that,

$$\mathbf{E}[\mathcal{P}(\mathcal{A}_1)] \geq \xi_1 \geq \frac{1}{\alpha_1} OPT_{N1}$$

and there exists, for instance $\mathcal{I}_2$, a polynomial-time non-adaptive algorithm $\mathcal{A}_2$, a polynomial-time computable quantity ξ_2 and a constant $\alpha_2 \geq 1$ such that,

$$\mathbf{E}[\mathcal{P}(\mathcal{A}_2)] \geq \xi_2 \geq \frac{1}{\alpha_2} OPT_{N2}$$

then there exists, for instance $\mathcal{I}$ a polynomial-time non-adaptive algorithm $\mathcal{A}$ such that,

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{\alpha_1 + \alpha_2} OPT_N$$

Chapter 4

Algorithms for Small Tasks

In this section we give approximation algorithms for the various special cases of sUfpTreeEdgeSubset for instances in which all tasks are small. As defined in §1.5, we say that a task t is small if $\mu_t \leq \delta b_t$.

4.1 Uniform Capacities

The following theorem gives an approximation for sRapTree instances where each task t corresponds to P_t which is a k-ary rooted subtree of tree G having its least depth vertex in G as root. We will use this result to obtain constant-factor approximations for sRapPath and sRAPT-kS and to obtain a constant-factor approximation to non-adaptive algorithms for sRAPkT-T.

Theorem 4.1.1 *When all capacties are equal (and scaled to 1), a task t is δ-small if $\mu_t \leq \delta$. Consider the sRapTree where each task $t \in T$ corresponds to P_t which is a k-ary rooted subtree of tree G having its least-depth vertex in G as root. For reals $p, \delta \in (0, 1)$ such that $\delta < p$, if all tasks are δ-small then there exists a non-adaptive scheduling algorithm $\mathcal{A}(\delta)$ for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A}(\delta))] \geq \frac{(1-p)(1-\frac{1}{p}\delta)}{2(k+1)^2}\phi(\mathbf{2}) \geq \frac{(1-p)(1-\frac{1}{p}\delta)}{2(k+1)^2}OPT$$

Proof. We will use randomized rounding on an optimal solution to $\phi(\mathbf{2})$ to obtain a constant-factor approximation.

Let $(x_1, \ldots, x_n)$ be a solution to $\mathcal{L}(\mathbf{2})$ for which the value of the objective function $\sum_{t \in T} \tilde{v}_t x_t$ equals $\phi(\mathbf{2})$. The idea is to schedule tasks t with probability proportional to x_t, with the constant of proportionality being sufficiently small to ensure that when each task is scheduled, there is at least a constant probability that all of its edges will have residual capacity at least a constant multiple of δ.

We define the sequence Y of random indicator variables, one for each item, as follows:

$$Y_t = \begin{cases} 1 & \text{with probablility } \frac{(1-\frac{1}{p}\delta)}{2(k+1)} x_t \\ 0 & \text{otherwise} \end{cases}$$

Algorithm: The algorithm $\mathcal{A}(\delta)$ proceeds as follows: It considers the tasks in the increasing order of their indices and attempts to schedule task t if $Y_t = 1$ and the task t is feasible at that point of time. Recall that the tasks are numbered in increasing order of the depth of the root of the subtree corresponding to them.

We define the sequence of random indicator variables Z as follows:

$$Z_t = \begin{cases} 1 & \text{if } Y_t = 1 \text{ and } \sum\limits_{\substack{t'<t \\ t' \in T_e}} s_{t'} Z_{t'} \leq 1 - 2\mu_t \text{ for all } e \in P_t \\ 0 & \text{otherwise} \end{cases}$$

Claim 4.1.2 $\Pr[Z_t = 1 | Y_t = 1] \geq \frac{1}{k+1}$

Claim 4.1.3 $\Pr[$*Task t is successfully scheduled* $| \; Z_t = 1] \geq 1 - p$

We will now show that

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We denote by $\mathcal{Y}(t, e)$ an expression which is an upper bound on the used up capacity on edge e at the stage where decisions on the first $t-1$ tasks have been made by $\mathcal{A}$. For $t \in T$ and $e \in E$ define

$$\mathcal{Y}(t, e) = \sum_{\substack{t'<t \\ t' \in T_e}} S_{t'} Y_{t'}$$

We introduce another analogous piece of notation. Define

$$\tilde{\mathcal{Y}}(t, e) = \sum_{\substack{t'<t \\ t' \in T_e}} \tilde{S}_{t'} Y_{t'}$$

If $Y_{t'} = 1$ and t' was feasible at the point in time when the first $t'-1$ decisions were made then $S_{t'}$ is well-defined since we know that an attempt was made to schedule task t'. We adopt the convention that if $Y_{t'} = 1$ and t' was not feasible at the point in time when the first $t'-1$ decisions were made then it was instantiated even though no attempt was made to insert it. Under this convention the expressions $\mathcal{Y}(t, e)$ and $\tilde{\mathcal{Y}}(t, e)$ are always well-defined.

Consider $t \in T$. Let x denote the root of P_t and let $f_1, \dots, f_{k'}$ denote the least-depth edges between x and each of its $k' (\leq k)$ children in P_t. Since we are processing tasks in top-down order of the roots of their corresponding subtrees and since all edges have equal capacities, one of $f_1, \dots, f_{k'}$ must have minimum remaining capacity among edges in P_t. We conclude that if $Z_t = 0$ and $Y_t = 1$ then there must exist an $i \in [1, k']$ such that

$$\mathcal{Y}(t, f_i) \geq \sum_{\substack{t'<t \\ t' \in T_{f_i}}} s_{t'} Z_{t'} > 1 - \frac{1}{p} \mu_t$$

From the union bound, we have

$$\Pr[Z_t = 0 | Y_t = 1] \leq \sum_{i=1}^{k'} \Pr[\mathcal{Y}(t, f_i) > 1 - \frac{1}{p} \mu_t]$$

Consider a particular $\mathcal{Y}(t, f_i)$ summation. If none of the $S_{t'}$ values which contribute to it are more than one then we can replace all of them by $\tilde{S}_{t'}$. If any of them is more than one then the inequality is guaranteed to be satisfied and again we can replace all $S_{t'}$ values with $\tilde{S}_{t'}$ values. Hence we can replace each $\mathcal{Y}(t, f_i)$ with $\tilde{\mathcal{Y}}(t, f_i)$

$$\begin{aligned}\Pr[Z_t = 0 | Y_t = 1] &\leq \sum_{i=1}^{k'} \Pr[\tilde{\mathcal{Y}}(t, f_i) > 1 - \frac{1}{p}\mu_t] \\ &\leq \sum_{i=1}^{k'} \Pr[\tilde{\mathcal{Y}}(t, f_i) > 1 - \frac{1}{p}\delta]\end{aligned}$$

The $Y_{t'}$ variables are independent from the $\tilde{S}_{t'}$ variables. Hence

$$\begin{aligned}\mathbf{E}[\tilde{\mathcal{Y}}(t, f_i)] &= \mathbf{E}[\sum_{\substack{t'<t \\ t' \in T_{f_i}}} \tilde{S}_{t'} Y_{t'}] \\ &= \sum_{\substack{t'<t \\ t' \in T_{f_i}}} \mathbf{E}[\tilde{S}_{t'}]\mathbf{E}[Y_{t'}] \\ &= \sum_{\substack{t'<t \\ t' \in T_{f_i}}} \mu_{t'} \cdot \frac{1 - \frac{1}{p}\delta}{2(k+1)} x_{t'} \\ &= \frac{1 - \frac{1}{p}\delta}{k+1} \cdot \sum_{\substack{t'<t \\ t' \in T_{f_i}}} \frac{\mu_{t'} x_{t'}}{2} \\ &\leq \frac{1 - \frac{1}{p}\delta}{k+1} \cdot \sum_{t' \in T_{f_i}} \frac{\mu_{t'} x_{t'}}{2} \\ &\leq \frac{1 - \frac{1}{p}\delta}{k+1}\end{aligned}$$

The last of the inequalities above follows from the set of constraints (L.1). We now apply Markov's inequality to infer that

$$\Pr[\tilde{\mathcal{Y}}(t, f_i) > 1 - \frac{1}{p}\delta] \leq \frac{1}{k+1}$$

Consequently

$$\begin{aligned}\Pr[Z_t = 0 | Y_t = 1] &\leq \sum_{i=1}^{k'} \Pr[\tilde{\mathcal{Y}}(t, f_i) > 1 - \frac{1}{p}\delta] \\ &\leq \frac{k'}{k+1} \\ &\leq \frac{k}{k+1}\end{aligned}$$

Hence

$$\Pr[Z_t = 1 | Y_t = 1] \geq \frac{1}{k+1}$$

Let us now find a lower bound for the probability of task t being successfully scheduled given that $Z_t = 1$. Consider the point in time when we have made the first $t-1$ decisions. Note that $Z_t = 1$ implies that $Y_t = 1$. It also implies that the used up capacity of every edge in P_t is at most $(1 - \frac{1}{p}\mu_t)$. The first consequence of this is that task t is feasible and an attempt will be made by $\mathcal{A}(\delta)$ to schedule it. The Markov inequality implies that $\Pr[\tilde{S}_t \geq \frac{1}{p}\mu_t] \leq p$ or equivalently $\Pr[\tilde{S}_t \leq \frac{1}{p}\mu_t] \geq 1-p$. Since $\mu_t \leq \delta < p$ we know that $\tilde{S}_t \leq \frac{1}{p}\mu_t < 1 \Rightarrow \tilde{S}_t = S_t$ from which we conclude $\Pr[S_t \leq \frac{1}{p}\mu_t] \geq 1-p$. This leads us to the second more important consequence:

$$\Pr[\text{Task } t \text{ is successfully scheduled}|Z_t = 1] \geq 1-p$$

Hence

$$\begin{aligned}
\Pr[\text{Task } t \text{ is successfully scheduled}] &= \Pr[Y_t = 1] \cdot \Pr[Z_t = 1|Y_t = 1] \\
&\cdot \Pr[\text{Task } t \text{ is successfully scheduled}|Z_t = 1, Y_t = 1] \\
&= \Pr[Y_t = 1] \cdot \Pr[Z_t = 1|Y_t = 1] \\
&\cdot \Pr[\text{Task } t \text{ is successfully scheduled}|Z_t = 1] \\
&\geq \frac{1 - \frac{1}{p}\delta}{2(k+1)} x_t \cdot \frac{1}{k+1} \cdot (1-p) \\
&= \frac{(1-p)(1-\frac{1}{p}\delta)}{2(k+1)^2} x_t
\end{aligned}$$

Thus the expected payoff from task t is at least $\frac{(1-2\delta)}{4(k+1)^2} v_t x_t$. Hence

$$\begin{aligned}
\mathbf{E}[\mathcal{P}(\mathcal{A})] &= \sum_{t \in T} v_t \Pr[\text{Task } t \text{ is successfully scheduled}] \\
&\geq \frac{(1-p)(1-\frac{1}{p}\delta)}{2(k+1)^2} \sum_{t \in T} v_t x_t \\
&\geq \frac{(1-p)(1-\frac{1}{p}\delta)}{2(k+1)^2} \sum_{t \in T} \tilde{v}_t x_t \\
&= \frac{(1-p)(1-\frac{1}{p}\delta)}{2(k+1)^2} \phi(\mathbf{2}) \\
&\geq \frac{(1-p)(1-\frac{1}{p}\delta)}{2(k+1)^2} OPT
\end{aligned}$$

This completes the proof of Theorem 4.1.1. ∎

4.2 Non-Uniform Capacities

The following theorem gives an approximation for instances of the sUFPT-kS under the NBA where all tasks are δ-small. We will use this result to obtain constant-factor approximations for the sUFPT-kS under the NBA. We can also use it to obtain constant-factor approximations under the NBA for the sUfpPath and the sUfpTree, since they are special cases of sUFPT-kS. However we will use better results (described later in this section) for these in order to attain a slightly better constant-factor.

Theorem 4.2.1 *Consider the sUFPT-kS under the NBA and let $\delta = 0.0005$. If all tasks are δ-small then there exists a nonadaptive scheduling algorithm $\mathcal{A}$ for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{822.37 \cdot k^{2.15}} OPT$$

Proof. As in the proof of Theorem 4.2.2, we will use randomized rounding on an optimal solution to $\phi(\mathbf{2})$ to obtain a constant-factor approximation.

Let $(x_1, \ldots, x_n)$ be a solution to $\mathcal{L}(\mathbf{c}+\mathbf{1})$ for which the value of the objective function $\sum_{t\in T} \tilde{v}_t x_t$ equals $\phi(\mathbf{c}+\mathbf{1})$. As in the proof of Theorem 4.2.2, the idea is to schedule tasks t with probability proportional to x_t, with the constant of proportionality being sufficiently small to ensure that when each task is scheduled, there is at least a constant probability that all of its edges will have residual capacity at least a constant multiple of δb_t.

We define a parameter $\alpha = 0.032/k^{2.15}$ and the sequence Y of random indicator variables, one for each item, as follows:

$$Y_t = \begin{cases} 1 & \text{with probablility } \frac{\alpha x_t}{2} \\ 0 & \text{otherwise} \end{cases}$$

Algorithm: The algorithm $\mathcal{A}$ proceeds as follows: It considers the tasks in the increasing order of their indices and attempts to schedule task t if $Y_t = 1$ and task t is feasible at that point of time. Recall that in this case the tasks are numbered in increasing depth of the root of the k-spiders corresponding to them.

We define the sequence of random indicator variables Z as follows:

$$Z_t = \begin{cases} 1 & \text{if } Y_t = 1 \text{ and } \sum\limits_{\substack{t'<t \\ t' \in T_e}} s_{t'} Z_{t'} \leq c_e - 2\mu_t \text{ for all } e \in P_t \\ 0 & \text{otherwise} \end{cases}$$

We will now show that

- $\Pr[Z_t = 1 | Y_t = 1] \geq 0.154$
- $\Pr[\text{Task } t \text{ is successfully scheduled} | Z_t = 1] \geq \frac{1}{2}$

Note: We continue using the $\mathcal{Y}(t, e)$ notation that we introduced in 4.1.1. The note in Theorem 4.1.1 about instantiation by convention is applicable here as well and accordingly $\mathcal{A}$ is essentially nonadaptive.

Consider $t \in T$. Let x denote the root of the k-spider P_t and let $P_{t,1} = (f_{1,1}, \ldots f_{1,g_1}), \ldots P_{t,k'} = (f_{k',1}, \ldots f_{k',g_{k'}})$ be the $k'(\leq k)$ edge-disjoint paths going down from x to the leaves of P_t such that $P_t = P_{t,1} \cup \ldots P_{t,k'}$.

Note that if $Z_t = 0$ and $Y_t = 1$ there exists $i \in [k'], b \in [g_i]$ such that

$$\mathcal{Y}(t, f_{i,b}) \geq \sum_{\substack{t'<t \\ t' \in T_{f_{i,b}}}} s_{t'} Z_{t'} \geq c_{f_{i,b}} - 2\mu_t$$

We will now define a maximal sequence of edges in each $P_{t,i}$ starting at $f_{i,1}$ in which the capacities decrease exponentially. Let us define the sequence $f_{i,1}, \ldots, f_{i,h_i}$ as follows:

$$e_{i,1} = f_{i,1}$$
$$e_{i,l} = \arg\min \left\{ \text{depth}(e) \,\middle|\, e \in P_{t,i} \text{ and } \text{depth}(e_{i,l-1}) < \text{depth}(e) \text{ and } c_e < \frac{c_{e_{i,l-1}}}{2} \right\} \text{ for } l \geq 2$$

We stop the construction of the sequence when no such e exists. We now define the event $\xi_{i,a}$ for $i \in [k'], a \in [h_i]$ as follows:

$$\xi_{i,a} : \mathcal{Y}(t, e_{i,a}) > \frac{1}{2} c_{e_{i,a}} - 2\mu_t$$

We will now show that $\Pr[Z_t = 0 | Y_t = 1] < \sum_{i \in [k']} \sum_{a \in [h_i]} \Pr[\xi_{i,a}]$. We have already noted that if $Z_t = 0$ given that $Y_t = 1$ then we must have $\mathcal{Y}(t, f_{i,b}) > c_{f_{i,b}} - 2\mu_t$ for some $i \in [k'], b \in [g_i]$. Consider some such i, b and let $a \in [h]$ be the largest index such that $depth(e_{i,a}) \leq depth(f_{i,b})$. Note that a is always well-defined because $e_{i,1} = f_{i,1}$. Observe that $\mathcal{Y}(t, e_{i,a}) \geq \mathcal{Y}(t, f_{i,b})$ since k-spiders which contain $f_{i,1}$ and $f_{i,b}$ must contain $e_{i,a}$. If the inequality $c_{f_{i,b}} < c_{e_{i,a}}/2$ was true then either $f_{i,b}$ or something of a lower depth would have been selected as $e_{i,a+1}$. We thus conclude that $c_{f_{i,b}} \geq c_{e_{i,a}}/2$ and hence that $\mathcal{Y}(t, e_{i,a}) \geq \mathcal{Y}(t, f_{i,b}) > c_{f_{i,b}} - 2\mu_t \geq c_{e_{i,a}}/2 - 2\mu_t$. We infer that if $Z_t = 0$ and $Y_t = 1$ then there exists $i \in [k'], a \in [h_i]$ such that the event $\xi_{i,a}$ occurs. It follows that $\Pr[Z_t = 0 | Y_t = 1] < \sum_{i \in [k']} \sum_{a \in [h_i]} \Pr[\xi_{i,a}]$.

Let us now upper bound the quantity $\Pr[\xi_{i,a}]$ using the Chernoff bound. We set the parameter $\beta = (1/2 - 2\delta - \alpha)/\alpha$. Observe that

$$\begin{aligned}
\beta &= \frac{0.5 - 0.001 - 0.032/k^{2.15}}{0.032/k^{2.15}} \\
&\geq \frac{0.467}{0.032} \cdot k^{2.15}
\end{aligned}$$

Let us define $\beta_0 = (0.467/0.032) \cdot k^{2.15}$, so that $\beta \geq \beta_0$. We use this estimate along and the inequality $\mu_t \leq \delta b_t \leq \delta c_{e_{i,a}}$ to obtain

$$\begin{aligned}
\Pr[\xi_{i,a}] &= \Pr[\mathcal{Y}(t, e_{i,a}) > \frac{1}{2} c_{e_{i,a}} - 2\mu_t] \\
&\leq \Pr[\mathcal{Y}(t, e_{i,a}) > \frac{1}{2} c_{e_{i,a}} - 2\delta c_{e_{i,a}}] \\
&= \Pr[\mathcal{Y}(t, e_{i,a}) > (1+\beta)\alpha c_{e_{i,a}}] \\
&\leq \Pr[\mathcal{Y}(t, e_{i,a}) > (1+\beta_0)\alpha c_{e_{i,a}}]
\end{aligned}$$

Also

$$\begin{aligned}
\mathbf{E}[\mathcal{Y}(t, e_{i,a})] &= \sum_{\substack{t' < t \\ t' \in T_{e_{i,a}}}} \mathbf{E}[s_{t'}]\mathbf{E}[Y_{t'}] \\
&= \frac{\alpha}{2} \sum_{\substack{t' < t \\ t' \in T_{e_{i,a}}}} \mu_{t'} x_{t'} \\
&\leq \frac{\alpha}{2} \sum_{t' \in T_{e_{i,a}}} \mu_{t'} x_{t'} \\
&\leq \frac{\alpha}{2} (c_{e_{i,a}} + 1) \\
&\leq \alpha c_{e_{i,a}}
\end{aligned}$$

Note that $\mathcal{Y}(t, e_{i,a})$ is the sum of independent random variables over $[0, 1]$ and hence we can use the Chernoff bound to obtain that

$$\begin{aligned}
\Pr[\xi_{i,a}] &\leq \Pr[\mathcal{Y}(t, e_{i,a}) > (1+\beta_0)\alpha c_{e_{i,a}}] \\
&\leq \Big(\frac{e^{\beta_0}}{(1+\beta_0)^{1+\beta_0}}\Big)^{\alpha c_{e_{i,a}}} \\
&\leq \Big(\frac{e}{\beta_0}\Big)^{\beta_0 \alpha c_{e_{i,a}}}
\end{aligned}$$

We substitute the values $\beta_0 = (0.467/0.032) \cdot k^{2.15}$ and $\alpha = 0.032/k^{2.15}$

$$\begin{aligned}
\Pr[\xi_{i,a}] &\leq \Big(\frac{0.187}{k^{2.15}}\Big)^{0.467 \cdot c_{e_{i,a}}} \\
&\leq \Big(\frac{0.458}{k}\Big)^{c_{e_{i,a}}}
\end{aligned}$$

Finally, we use this result to upper bound $\Pr[Z_t = 0|Y_t = 1]$. We know that $c_{e_{i,a}} > 2c_{e_{i,a+1}}$ for all $a \in [h-1]$ and that $c_{e_{i,h_i}} \geq 1$. Hence

$$\begin{aligned}
\Pr[Z_t = 0|Y_t = 1] &\leq \sum_{i \in [k']} \sum_{a=1}^{h_i} \Pr[\xi_{i,a}] \\
&\leq \sum_{i \in [k']} \sum_{a=1}^{h_i} \Big(\frac{0.458}{k}\Big)^{c_{e_a}} \\
&\leq \sum_{i \in [k']} \sum_{j=0}^{\infty} \Big(\frac{0.458}{k}\Big)^{2^j} \\
&\leq \sum_{i \in [k']} \sum_{j=0}^{\infty} \Big(\frac{0.458}{k}\Big)^{j} \\
&\leq k' \cdot \Big(\frac{\frac{0.458}{k}}{1 - \frac{0.458}{k}}\Big) \\
&\leq k \cdot \Big(\frac{\frac{0.458}{k}}{1 - 0.458}\Big) \\
&\leq 0.846
\end{aligned}$$

It follows that

$$\Pr[Z_t = 1|Y_t = 1] \geq 0.154$$

Let us now find a lower bound for the probability of task t being successfully scheduled given that $Z_t = 1$. Note that $Z_t = 1$ implies that $Y_t = 1$. It also implies that $\mathcal{Y}(t, e) \leq c_e - 2\mu_t$ for every edge $e \in P_t$. The first consequence of this is that task t is feasible and an attempt will be made by $\mathcal{A}$ to schedule it. The Markov inequality implies that $\Pr[s_t > 2\mu_t] < \frac{1}{2}$ or equivalently $\Pr[s_t \leq 2\mu_t] \geq \frac{1}{2}$. This leads us to the second more important consequence:

$$\Pr[\text{Task } t \text{ is successfully scheduled}|Z_t = 1] \geq \frac{1}{2}$$

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Hence

$$\begin{aligned}\Pr[\text{Task } t \text{ is successfully scheduled}] &= \Pr[Y_t = 1] \cdot \Pr[Z_t = 1 | Y_t = 1] \\ &\cdot \Pr[\text{Task } t \text{ is successfully scheduled} | Z_t = 1, Y_t = 1] \\ &= \Pr[Y_t = 1] \cdot \Pr[Z_t = 1 | Y_t = 1] \\ &\cdot \Pr[\text{Task } t \text{ is successfully scheduled} | Z_t = 1] \\ &\geq \frac{\alpha x_t}{2} \cdot 0.154 \cdot \frac{1}{2} \\ &\geq 0.038\alpha \cdot x_t\end{aligned}$$

Thus the expected payoff from task t is at least $\frac{0.232\alpha}{4} v_t x_t$. Hence

$$\begin{aligned}\mathbf{E}[\mathcal{P}(\mathcal{A})] &= \sum_{t \in T} v_t \Pr[\text{Task } t \text{ is successfully scheduled}] \\ &\geq 0.038\alpha \cdot \sum_{t \in T} v_t x_t = 0.038\alpha \cdot \phi(\mathbf{c} + \mathbf{1}) \\ &= 0.038\alpha \cdot OPT \\ &\geq \frac{1}{822.37 \cdot k^{2.15}} \cdot OPT\end{aligned}$$

This completes the proof of Theorem 4.2.1. ∎

4.2.1 An Improved Constant for sUfpPath

Note that the sUfpPath is the special case of sUFPT-kS where G is a path rooted at one of its endpoints and $k = 1$. Hence we can obtain a constant-factor approximation for instances of the sUfpPath in which all tasks are small using Theorem 4.2.1. However, in Theorem 4.2.1 we use several loose upper bounds, including one in which we approximated $\sum_{j \geq 0} z^{2^j}$ by $\sum_{j \geq 0} z^j$. The following theorem gives a better approximation factor to sUfpPath than the $1/822.37$ factor guaranteed by Theorem 4.2.1. Its proof is nearly identical to Theorem 4.2.1 and so only the parts of the calculations which are different are stated here so as to avoid repetition.

Theorem 4.2.2 *Consider the sUfpPath under the NBA and let $\delta = 0.0005$. If all tasks are δ-small then there exists a nonadaptive scheduling algorithm $\mathcal{A}$ for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{310.18} OPT$$

Proof. As stated above, this proof is nearly identical to that of Theorem 4.2.1 we will only state here a few calculations which differ from the proof of Theorem 4.2.1.

As before we define the constants $\alpha = 0.032$ and $\beta = (1/2 - 2\delta - \alpha)/\alpha$. We obtain

$$\Pr[\xi_{1,a}] \leq \left(\frac{e^\beta}{(1+\beta)^{1+\beta}} \right)^{\alpha c_{e_{1,a}}} \leq (0.4051)^{c_{e_{1,a}}}$$

This leads to

$$\Pr[Z_t = 0 | Y_t = 1] \leq \sum_{a=1}^{h_1} \Pr[\xi_{1,a}] \leq \sum_{j=0}^{\infty} (0.4051)^{2^j} \leq 0.597$$

which implies

$$\Pr[Z_t = 1 | Y_t = 1] \geq 0.403$$

Consequently

$$\Pr[\text{Task } t \text{ is successfully scheduled}] \geq \frac{\alpha x_t}{2} \cdot 0.403 \cdot \frac{1}{2} = \frac{0.403\alpha}{4} x_t$$

Finally, we obtain

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{0.403\alpha}{4} OPT \geq \frac{1}{310.18} OPT$$

∎

The sUfpTree is the special case of sUFPT-kS where $k = 2$. Like the sUfpPath, we can obtain a constant-factor approximation for instances of the sUfpTree in which all tasks are small using Theorem 4.2.1. However, the loose upper bounds used in Theorem 4.2.1 give us an approximation factor of $1/(822.37 \cdot 2^{2.15}) = 1/3649.91$. We will state a theorem here which attains a better approximation factor. As in Theorem 4.2.2, the proof is nearly identical to Theorem 4.2.1 and so only the parts of the calculations which are different are stated here so as to avoid repetition.

4.2.2 An Improved Constant for sUfpTree

Theorem 4.2.3 *Consider the sUfpTree under the NBA and let $\delta = 0.0005$. If all tasks are δ-small then there exists a nonadaptive scheduling algorithm $\mathcal{A}$ for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{1077.59} \cdot \phi(\mathbf{c} + \mathbf{1}) \geq \frac{1}{1077.59} \cdot OPT$$

Proof. Along the lines of Theorem 4.2.2 we will only state here a few calculations which differ from the proof of Theorem 4.2.1.

As before we define the constants $\alpha = 0.016$ and $\beta = (1/2 - 2\delta - \alpha)/\alpha$. We obtain

$$\Pr[\xi_{i,a}] \leq \left(\frac{e^{\beta}}{(1+\beta)^{1+\beta}}\right)^{\alpha c_{e_{i,a}}} \leq (0.2913)^{c_{e_{i,a}}}$$

This leads to

$$\Pr[Z_t = 0 | Y_t = 1] \leq \sum_{i=1}^{2} \sum_{a=1}^{h_1} \Pr[\xi_{i,a}] \leq \sum_{i=1}^{2} \sum_{j=0}^{\infty} (0.2913)^{2^j} \leq 0.768$$

which implies

$$\Pr[Z_t = 1 | Y_t = 1] \geq 0.232$$

Consequently

$$\Pr[\text{Task } t \text{ is successfully scheduled}] \geq \frac{\alpha x_t}{2} \cdot 0.232 \cdot \frac{1}{2} = \frac{0.232\alpha}{4} x_t$$

Finally, we obtain

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{0.232\alpha}{4} OPT \geq \frac{1}{1077.59} OPT$$

∎

Chapter 5

Algorithms for Large Tasks

In this section we will give results for instances of special cases of sUfpTreeEdgeSubset in which all tasks are δ-large. These results when combined according to §3 with algorithms in §4 will result in approximation algorithms for the various special cases of sUfpTreeEdgeSubset that we are concerned with. Recall that a task t is δ-large if $\mu_t > \delta b_t$.

5.1 Uniform Capacities

When all capacities are equal (and scaled to 1), a task t is δ-large if $\mu_t > \delta$. Lemma 5.1.1 states that for instances of the sRapTree in which each task corresponds to a subtree and all tasks are δ-large, $\phi'(\mathbf{1})$ is within a constant factor of $\phi(\mathbf{2})$. Recall that $\phi(\mathbf{u})$ and $\phi'(\mathbf{u})$ are the values of the optimal solutions to the linear programs $\mathcal{L}(\mathbf{u})$ and $\mathcal{L}'(\mathbf{u})$ defined in §2.1.

Lemma 5.1.1 *Consider the sRapPath in which all tasks correspond to subtrees. For positive $\delta \leq 1$, if all tasks are δ-large then*

$$\phi'(\mathbf{1}) \geq \frac{\delta}{2}\phi(\mathbf{2})$$

Proof. Let $(x_1, \ldots, x_n)$ be an optimal solution to $\mathcal{L}(\mathbf{2})$. Then note that $(x_1/2, \ldots, x_n/2)$ is a feasible solution to $\mathcal{L}(\mathbf{1})$ under which the value of the objective function is $\phi(\mathbf{2})/2$. Hence

$$\phi(\mathbf{1}) \geq \frac{1}{2}\phi(\mathbf{2})$$

Now let $(x_1, \ldots, x_n)$ be an optimal solution to $\mathcal{L}(\mathbf{1})$. For each task t define $x'_t = \delta x_t$. For any processor e we have that $\sum_{t \in T_e} x'_t = \sum_{t \in T_e} \delta x_t < \sum_{t \in T_e} \mu_t x_t \leq 1$. We infer that the solution $(x'_1, \ldots x'_n)$ is a feasible solution to $\mathcal{L}'(\mathbf{1})$. Under this solution the objective function has the value $\delta\phi(\mathbf{1})$. Hence

$$\phi'(\mathbf{1}) \geq \delta\phi(\mathbf{1})$$

This completes the proof of Lemma 5.1.1. ∎

Theorem 5.1.2 obtains a constant-factor approximation for the sRapPath when all tasks are δ-large and will be used in the analysis of constant-factor approximation algorithms for sRapPath.

Theorem 5.1.2 *Consider the sRapPath. For positive $\delta \leq 1$, if all tasks are δ-large then there exists a polynomial-time non-adaptive scheduling algorithm $\mathcal{A}(\delta)$ for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A}(\delta))] \geq \phi'(\mathbf{1}) \geq \frac{\delta}{2}\phi(\mathbf{2}) \geq \frac{\delta}{2}OPT.$$

Proof. Consider the constraint matrix corresponding to the linear program $\mathcal{L}'(\mathbf{1})$ defined in §2.1. All entries of this matrix are either 0 or 1. Furthermore, each column t has a contiguous sequence of entries all of which are 1s and the rest of its entries are 0s. The consecutive-ones property implies the existence of an optimal solution to $\mathcal{L}'(\mathbf{1})$ that is also integral; this is because the constraint matrix is totally-unimodular [**?**, Theorem blahblah]. Let $(x'_1, \ldots, x'_n)$ be such a solution and let $A' = \{t \in T | x'_t = 1\}$. Observe that since all the x'_t values are integral, the constaints of $\mathcal{L}'(\mathbf{1})$ imply that the set A' is an independent set of the interval graph underlying the stochastic RAP instance.

This leads to the following algorithm which we will denote by $\mathcal{A}$: Find a maximum weighted independent set A of the interval graph formed by the set of intervals $P_t = [a_t, b_t)$ having weight $\tilde{v}_t$ for each task t. Schedule the tasks in A in arbitrary order.

Since the intervals corresponding to the tasks in A are disjoint, each processor in P_t will have residual capacity 1 at the time that task t is scheduled. Thus the probability that task t is successfully scheduled is $\Pr[s_t \leq 1]$ and the expected payoff due to task t is $v_t \Pr[s_t \leq 1] = \tilde{v}_t$. Hence, using Lemma 5.1.1 we infer that

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] = \sum_{t \in A} \tilde{v}_t \geq \sum_{t \in A'} \tilde{v}_t = \sum_{t \in T} \tilde{v}_t x'_t = \phi'(\mathbf{1}) \geq \frac{\delta}{2}\phi(\mathbf{2}) \geq \frac{\delta}{2} OPT$$

This completes the proof of Theorem 5.1.2. ∎

Let us now consider the sRAPT-kS. We will prove in Theorem 5.2.3 that the integrality gap of $\mathcal{L}'(\mathbf{u})$ for sUFPT-kS instances is $2k$. Using this and Lemma 5.1.1, we now prove Theorem 5.1.3 which gives a constant factor approximation for sRAPT-kS instances in which all tasks are δ-large.

Theorem 5.1.3 *Consider the sRAPT-kS. For positive $\delta \leq 1$, if all tasks are δ-large then there exists a polynomial-time non-adaptive scheduling algorithm $\mathcal{A}$ for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{\delta}{4k} OPT$$

Proof. We have shown in Theorem 5.2.3 that $\mathcal{L}'(\mathbf{1})$ has an integral solution for which the value of the objective function is at least $\phi'(\mathbf{1})/(2k)$. Let $(x'_1, \ldots, x'_n)$ be such a solution and let $A = \{t \in T | x'_t = 1\}$. Observe again, as in the proof of Theorem 5.1.2, that since all the x'_t values are integral, the constaints of $\mathcal{L}'(\mathbf{1})$ imply that the set A is an independent set of the interval graph underlying the stochastic RAP instance.

As in the proof of Theorem 5.1.2, we observe that since the tasks in A are edge-disjoint the expected payoff due to task t is $v_t \Pr[s_t \leq 1] = \tilde{v}_t$. From Lemma 5.1.1, we infer that

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] = \sum_{t \in A} \tilde{v}_t = \sum_{t \in T} \tilde{v}_t x'_t = \frac{1}{2k}\phi'(\mathbf{1}) \geq \frac{\delta}{4k}\phi(\mathbf{2}) \geq \frac{\delta}{4k} OPT$$

This completes the proof of Theorem 5.1.3. ∎

5.2 Non-Uniform Capacities

Lemma 5.2.1, which is similar to Lemma 5.1.1, states that for instances of the sUfpTree in which each task corresponds to a subtree and is δ-large, $\phi'(\lfloor \mathbf{c} \rfloor)$ is within a constant factor of $\phi(\mathbf{c} + \mathbf{1})$. Recall that $\phi(\mathbf{u})$ and $\phi'(\mathbf{u})$ are the values of the optimal solutions to the linear programs $\mathcal{L}(\mathbf{u})$ and $\mathcal{L}'(\mathbf{u})$ defined in §2.1. We will use Lemma 5.2.1 to obtain a constant factor approximation for sUfpPath when all tasks are large.

Lemma 5.2.1 *Consider the* sUfpGeneral *under the* NBA *in which all tasks correspond to subtrees. For positive* $\delta \leq 1$*, if all tasks are* δ*-large then*

$$\phi'(\lfloor \mathbf{c} \rfloor) \geq \frac{\delta}{3}\phi(\mathbf{c}+\mathbf{1})$$

Proof. Let $(x_1, \ldots, x_n)$ be an optimal solution to $\mathcal{L}(\mathbf{c}+\mathbf{1})$. Then note that $(x_1/3, \ldots, x_n/3)$ is a feasible solution to $\mathcal{L}(\lfloor \mathbf{c} \rfloor)$ since for all $e \in E$, $c_e \geq 1$ and consequently $\lfloor c_e \rfloor \geq (c_e+1)/3$. The value of the objective function under this solution is $\sum_{t \in T} \tilde{v}_t x_t/3 = \phi(\mathbf{c}+\mathbf{1})/3$. Hence

$$\phi(\lfloor \mathbf{c} \rfloor) \geq \frac{1}{3}\phi(\mathbf{c}+\mathbf{1})$$

Note that $\mu_t > \delta b_t \geq \delta$. It follows from an argument similar to the one used in Lemma 5.1.1 that

$$\phi'(\lfloor \mathbf{c} \rfloor) \geq \delta\phi(\lfloor \mathbf{c} \rfloor)$$

This completes the proof of Lemma 5.2.1. ∎

Theorem 5.2.2 gives an approximation for instances of sUfpPath under the NBA where all tasks are δ-large. Notably, it guarantees that the payoff (and not its expectation) is within at most a constant-factor of the optimal payoff.

Theorem 5.2.2 *Consider the* sUfpPath *under the* NBA*. For positive* $\delta \leq 1$*, if all tasks are* δ*-large then there exists a non-adaptive scheduling algorithm* $\mathcal{A}$ *for which*

$$\mathcal{P}(\mathcal{A}) \geq \phi'(\lfloor \mathbf{c} \rfloor) \geq \frac{\delta}{3}\phi(\mathbf{c}+\mathbf{1}) \geq \frac{\delta}{3}OPT$$

Proof. Consider the constraint matrix corresponding to the linear program $\mathcal{L}'(\lfloor \mathbf{c} \rfloor)$ defined in §2.1. As in Theorem 5.1.2 we infer from the consecutive-ones property that this matrix is totally-unimodular and consequently that it has an optimal solution which is integral. Let $(x'_1, \ldots, x'_n)$ be such a solution and let $A = \{t \in T | x'_t = 1\}$.

Consider the algorithm $\mathcal{A}$ which schedules the tasks in A in arbitrary order. Since we are operating under the NBA and since we scaled the capacities so that $c_{\min} = 1$, we know that $S_t \leq 1$. Consequently, we have that for every edge e

$$\sum_{t \in A_e} S_t = \sum_{t \in T_e} S_t x'_t \leq \sum_{t \in T_e} x'_t \leq \lfloor c_e \rfloor$$

Hence

$$P(\mathcal{A}) = \sum_{t \in A} v_t = \sum_{t \in T} v_t x'_t = \phi'(\lfloor \mathbf{c} \rfloor) \geq \frac{\delta}{3}\phi(\mathbf{c}+\mathbf{1}) \geq \frac{\delta}{3}OPT$$

This completes the proof of Theorem 5.2.2. ∎

We will now proceed to prove sUFPT-kS. Towards this end, Theorem 5.2.3 establishes a constant-factor approximation algorithm for the UFPT-kS with unit-demands and integral capacities. This algorithm is a straightforward generalization of the approximation algorithm for the UFPT with unit-demands and integral capacities in ≪**Archit 5.2.0.1:** Reference: Chekuri-Mydlarz-Shephard≫. **AK 5.2.0.1** We note in passing, that as in the ≪**Archit 5.2.0.2:** Reference: Chekuri-Mydlarz-Shephard≫ paper, **AK 5.2.0.2** we can use Theorem 5.2.3 to establish a constant-factor approximation for UFPT-kS with integral capacities and integral demands.

Theorem 5.2.3 *For the sUFPT-kS, then the integrality gap of $\mathcal{L}'(\mathbf{c})$ is at most $2k$. Furthermore, there exists a polynomial time algorithm which can find a $2k$-approximate integral solution to $\mathcal{L}'(\mathbf{c})$.*

Proof. Let $\mathbf{x}' = (x'_1, \ldots, x'_n)$ be an optimal solution to $\mathcal{L}'(\mathbf{c})$. Let h be an integer such that $h\mathbf{x}'$ is an integral vector. Consider a set of tasks $\tilde{T}$ which has hx'_t replicas ef every task t in T. We will show that there exists a $2kh$-colouring of tasks in $\tilde{T}$ each of which is feasible such that no two edge replicas are coloured the same. Assuming that we have shown this, we infer that the sum of the payoffs of these $2kh$ colourings equals $h\phi'(\mathbf{c})$. Hence, the feasible set of tasks corresponding to at least one of these colourings must have payoff $\phi'(\mathbf{c})/(2k)$. It follows that $\mathcal{L}'(\mathbf{c})$ has an integrality gap of atmost $2k$.

To show the existence of such a $2kh$-colouring, we claim the following, which following the nomenclature in ≪**Archit 5.2.0.3:** Reference: Chekuri-Mydlarz-Shephard≫, we will refer to as the **bin-colouring claim**: AK 5.2.0.3

Consider a capacitated graph $G' = (V', E')$ which is a rooted tree and a set of tasks T' such that each task $t \in T'$ corresponds to the k-spider P'_t in G'. If

(i) $|T'_e| \leq hc_e$ for all $e \in E'$.

(ii) For each leaf l having edge e connecting it to its parent, the set of tasks T'_e are partitioned into atmost c_e bins at l, each having size between $[1, 2h)$.

(iii) The leaves of the k-spiders corresponding to each task are all distinct leaves of G' and the root has exactly one child.

then there exists a colouring of the edges which

(iv) Uses at most $2kh$ colours.

(v) Ensures that for each leaf, all the tasks in each bin are all coloured differently.

(vi) Ensures that for each colour d and each edge e, $|\{t \in T'_e | colour(t) = d\}| \leq c_e$.

We induct on the number of vertices in the tree. Our base case occurs when the root is the only non-leaf node in the tree. In this case, since it has exactly one child, there must be a single leaf l in the tree. This implies that all the k-spiders must be 1-spiders. Let e denote the only edge in the tree. Let $B_1, \ldots, B_r$ denote the bins at l. Colour the tasks in bin B_i with colours $1, \ldots, |B_i|$. Clearly, this colouring satisfies (v). Since the sizes of the bins are less than $2h$, we infer that it also satisfies (iv). Finally, since r is less than or equal to c_e, we infer that it satisfies (vi).

Otherwise, consider v, a deepest non-leaf node in the tree. Let us denote its set of its children, all of which are leaves, by $L = \{l_1, \ldots, l_z\}$. We collapse all the children of v and v itself into a single vertex to obtain a smaller instance $G'' = (V'', E'')$ and a set of tasks T''. Here $V'' = V' \setminus L$. E'' is the restriction of E' to V''. Let $\widetilde{T'}$ denote set of those tasks $t \in T'$ for which all leaves of P'_t belong to L. Then $T'' = T' \setminus \widetilde{T'}$. The vertex v is a leaf in G''. Let e denote the edge connecting v to its parent. To partition T''_e into the bins at v in the smaller instance, we consider the set of sets $B_e \setminus \widetilde{T'}$ for each bin B at each leaf in L. Let us denote this set of sets by U. First, we observe that the sets in U are mutually disjoint. This is because every task t in T''_e must be such that P'_t has exactly one of its leaves in L, since if P'_t had more than one leaf belonging to L, then the definition of a k-spider would imply that all of its leaves would necessarily belong to L. Having made this observation, we create a new bin at v for all sets in U whose sizes are in the range $[h, 2h)$. We will combine the sets in U having size $[1, h)$ into bins at v. We combine these serially in arbitrary order and start a new bin at v once the current bin's size equals or exceeds h. We stop when we run out of bins in U to combine. This process guarantees that each bin at v, except possibly the last one, has size in the range $[h, 2h)$. We know from (i) that $|T''_e| = |T'_e| \leq hc_e$. Hence the number of bins at v is at most c_e and we infer that the smaller instance satisfies (ii). It trivially satisfies (i) since $T'' \subseteq T'$. The smaller instance satisfies (iii) since we replaced exactly one leaf of each task $t \in T'_e$ with v which was not a leaf in G'.

From the inductive hypothesis we know that there exists a $2kh$-colouring for the set of tasks T'' in the smaller instance G'' which satisfies (iv), (v) and (vi). We extend this colouring to T', letting the colours assigned to tasks in T'' remain unchanged and appropriately assigning colours to the tasks in $\widetilde{T}'$. We know that for every bin B at every leaf L in G' the tasks in $B_e \setminus \widetilde{T}'$ were all assigned to the same bin at v, and hence were coloured differently. We conclude that all tasks in T'' which fall in the same bin at some leaf in L are coloured differently. It remains to colour the tasks in $\widetilde{T}'$ so that (iv) and (v) are satisfied. Consider tasks in $\widetilde{T}'$ in any order. The k-spider P_t for each such task t has atmost k leaves. Task t falls into some bin at each of these leaves. Each such bin has at most $2h-1$ tasks and since t is not yet coloured, the total number of colours used by all the bins together is atmost $k(2h-2) = 2kh - 2k$. We colour t with any one of the $2k$ unused colours, thereby ensuring that this colouring of tasks in T' satisfies (iv) and (v). It follows from the inductive hypothesis that this colouring of tasks in T' satisfies (vi) for all edges except those connecting a vertex in L to v. Let e_i denote the edge between v and l_i. Each task in T'_{l_i} must be in some bin at l_i. Since there are atmost c_{e_i} bins at l_i and the tasks in each bin are coloured differently, we infer that there are at most c_{e_i} tasks of any given colour in T'_{l_i}. Thus, this coloring satisfies (vi). This completes the induction and the proof of the bin-colouring claim.

The only thing still left to show is that the bin-colouring of tasks in T does not result in any two replicas of any task $t \in T$ being assigned the same colour. To ensure this, we allocate tasks to bins such that all replicas of each task $t \in T$ fall into the same bin at all endpoints of their corresponding k-spiders. The binning process is similar to the process of binning we followed in the smaller instance G'' in the inductive step. Consider groups of replicas of tasks incident to leaf l, connected to its parent with edge e. We consider these groups sequentially in arbitrary order and group them into bins at l, starting a new bin when the size of the current bin equals or exceeds h. We know from the LP-constraint $(L'.2)$ that the $|T_e| \leq hc_e$. The binning procedure described above ensures that all bins except possibly the last one have sizes in the range $[h, 2h)$ and hence that the number bins is atmost c_e. We conclude that this binning process satisfies (i) and (ii) and ensures that all replicas of every task are coloured differently, completing the proof.

We now use Theorem 5.2.3 to obtain a constant-factor approximation algorithm for δ-large instances of sUFPT-kS. Note, once again, that Theorem **??** guarantees that the payoff (and not its expectation) is within at most a constant-factor of the optimal payoff.

Theorem 5.2.4 *Consider the sUFPT-kS under the NBA. For positive $\delta \leq 1$, if all tasks are δ-large then there exists a nonadaptive scheduling algorithm $\mathcal{A}$ for which*

$$\mathcal{P}(\mathcal{A}) \geq \frac{\delta}{2k}\phi'(\lfloor \mathbf{c} \rfloor) \geq \frac{\delta}{6k}\phi(\mathbf{c}+\mathbf{1}) \geq \frac{\delta}{6k}OPT$$

Proof. We have shown in Theorem 5.2.3 that $\mathcal{L}'(\lfloor \mathbf{c} \rfloor)$ has an integral solution for which the value of the objective function is at least $\phi'(\lfloor \mathbf{c} \rfloor)/(2k)$. Let $(x'_1, \ldots, x'_n)$ be such a solution and let $A = \{t \in T | x'_t = 1\}$.

Consider the algorithm $\mathcal{A}$ which schedules the tasks in A in arbitrary order. Since we are operating under the NBA and since we scaled the capacities so that $c_{\min} = 1$, we know that $S_t \leq 1$.

Consequently, we have that for every edge e

$$\sum_{t \in A_e} S_t = \sum_{t \in T_e} S_t x'_t \leq \sum_{t \in T_e} x'_t \leq c_e$$

Hence

$$P(\mathcal{A}) = \sum_{t \in A} v_t = \sum_{t \in T} v_t x'_t \geq \frac{\delta}{2k}\phi'(\lfloor \mathbf{c} \rfloor) \geq \frac{\delta}{6k}\phi(\mathbf{c}+\mathbf{1}) \geq \frac{\delta}{6k}OPT$$

This completes the proof of Theorem **??**. □

5.3 sRAPkT-T: An approximation to non-adaptive algorithms

This section gives a polynomial-time constant-factor approximation to non-adaptive algorithms for sRAPkT-T. It is separated from §5.1 even though it deals with uniform capacities because the argument is of a different nature, providing an approximation not to a linear program but directly to an optimal non-adaptive algorithm.

Let OPT_N denote the expected payoff of an optimal non-adaptive algorithm. We will first sketch a $O(mn2^k)$ algorithm $\mathcal{A}$ which finds an optimal integral solution to $\phi'(\mathbf{1})$ and then show that the expected payoff of the algorithm which schedules the tasks selected by $\mathcal{A}$ in arbitrary order is within a constant factor of OPT_N.

Theorem 5.3.1 *There exists an algorithm for sRAPkT-T which finds an optimal integral solution to $\phi'(\mathbf{1})$ and runs in time $O((m+n)2^k)$.*

Proof. Note that an optimal integral solution to $\phi'(\mathbf{1})$ is also an optimal solution to the sRAPkT-T instance on the same capacitated graph in which each task t has deterministic payoff $\tilde{v}_t$. We will denote the tasks in this deterministic instance by $\mathcal{T}$. Further, for $v \in V$ we denote by $\mathcal{T}_v$ the set of tasks t in $\mathcal{T}$ such that P_t is completely contained in the subtree rooted at v.

Let $dp[v][t]$ denote the payoff of the optimal solution for the set of tasks $\mathcal{T}_v$ where the edge connecting v to its parent is covered with task $t \in \mathcal{T} \cup \{0\}$. Here $dp[v][0]$ denotes the optimal payoff when the edge connecting u to its parent is unused. The payoff of task t is not included in the DP value.

Denote the set of children of vertex v by C_v and the tasks in $\mathcal{T}_v \setminus \bigcup_{c \in C_v} \mathcal{T}_c$ by $t_{v,1} \dots t_{v,n_v}$. Note that $\{t_{v,1} \dots t_{v,n_v}\}$ is the set of tasks in $\mathcal{T}$ having v as root. For $v \in V$, $i \in [0, n_v]$, $C \subseteq C_v$, let $cdp[v][i][C]$ denote the payoff of the optimal solution for those among the first i tasks having v as root which are completely contained (besides vertex v) in the subtrees rooted at vertices in C and those tasks in $\mathcal{T}$ which are completely contained in the subtrees rooted at vertices in C. Formally $cdp[v][i][C]$ is the optimal solution for the set of tasks $\left(\bigcup_{c \in C} \mathcal{T}_c\right) \cup \{t_{v,i'} | i' \in [i] \text{ and } C_v \cap P_{t_{v,i'}} \subseteq C\}$.

We have the recurrences:

$$cdp[v][0][C] = \sum_{c \in C} dp[c][0]$$

$$cdp[v][i][C] = \begin{cases} cdp[v][i-1][C] & \text{if } C_v \cap P_{t_{v,i}} \not\subseteq C \\ \max\big(cdp[v][i-1][C], & \\ \qquad cdp[v][i-1][C \setminus P_{t_{v,i}}] + w_{t_{v,i}} + \sum_{c \in C_v \cap P_{t_{v,i}}} dp[c][t_{v,i}]\big) & \text{if } C_v \cap P_{t_{v,i}} \subseteq C \end{cases}$$

$$dp[v][t] = cdp[v][n_v][C_v \setminus P_t]$$

The recurrences above results in a $O((m+n)2^k)$ using precomputation of the summations in the computation of the *cdp* values. The payoff of the optimal solution is $dp[r][0]$ where r is the root. We can find an optimal solution by tracing the *dp* and *cdp* values.

Lemma 5.3.2 *Consider a rooted k-ary tree $G' = (V', E')$ and a set of subtrees T' of G'. If $i \in N$ is such that $|T'_e| \leq i$ for all $e \in E$ then T' can be partitioned into atmost $k(i-1)+1$ edge-disjoint subsets.*

Proof. The proof is constructive. WLG, assume that the tasks in T' are numbered $1, \ldots, n$ in non-decreasing order of the depth in G of their least-depth vertex. In the j^{th} iteration, initialize the current partition Q_j as the empty set. Iterate over the unpartitioned tasks in increasing order and add each such task to partition Q_j if adding it does not violate the edge-disjointness of Q_j. Stop when all tasks have been partitioned.

If there are more than $k(i-1)+1$ iterations, this means that at least one task t must be unclassified after the completion of $k(i-1)+1$ iterations. This task was not included in the j^{th} iteration because some edge in P_t was already used by Q_j. Let e_j be one such edge. If there are multiple candidates, choose any one with the least depth. Let v be the least-depth vertex of t. Since each iteration considers the tasks in increasing order, e_j must be one of the edges from the v to its children. Since G is a k-ary tree there are at most k such edges. The box principle implies that at least i of the elements in the sequence $(e_j)_{j \in [k(i-1)+1]}$ values must be identical. Since the Q_j's are disjoint, we infer that i tasks besides task t all pass through some edge e in P_t. Thus $|T'_e| \geq i+1$, a contradiction. ∎

Theorem 5.3.3 *Consider the sRAPkT-T. Consider $\delta = 0.6$. If all tasks are δ-large then there exists a nonadaptive scheduling algorithm $\mathcal{A}$ for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{225k+26} \cdot OPT_N$$

Proof. Consider a non-adaptive algorithm $\mathcal{A}'$. Let $t_1, \ldots, t_s$ be the sequence of tasks that it schedules, skipping only past the ones which become infeasible in the process. Let us the denote by T^i the set of the first i tasks scheduled by $\mathcal{A}'$. Formally $T^i = \{t_{i'} | i' \in [i]\}$. Consider that the tasks scheduled stack up over each other at each edge, independently of the other edges. We define the level l_i of task t_i as the number of tasks stacked up at the most stacked up edge in P_{t_i} just after adding the task t_i. Formally $l_i = \max\{|T^i_e| | e \in P_{t_i}\}$. Let L^i denote the set of tasks at level i. Let us define the random variable $\mathcal{P}_i(\mathcal{A}')$ as the payoff from tasks in L^i under the scheduling scheme of $\mathcal{A}'$.

From the linearity of expectation, we have that

$$\mathbf{E}[\mathcal{P}(\mathcal{A}')] = \sum_{i \geq 1} \mathbf{E}[\mathcal{P}_i(\mathcal{A}')]$$

Note that $|L^i_e| \leq i$ for all e, since otherwise the last of the tasks in L^i_e to be scheduled would be at level $i+1$ or more, a contradiction. From Lemma 5.3.2 it follows that the set of tasks in L_i can be partitioned into atmost $k(i-1)+1$ (denoted hereafter by $f(i)$) edge-disjoint sets. We know that for all tasks t, $\mu_t = \mathbf{E}[\tilde{s}_t] \geq 0.6$. We know that $\tilde{s}_t \leq 1$. If $\Pr[\tilde{s}_t \leq 1/2] > 0.8$, then we would have $\mathbf{E}[\tilde{s}_t] = \mu_t < 0.8 \cdot \frac{1}{2} + 0.2 \cdot 1 = 0.6$, a contradiction. Hence we know that $\Pr[\tilde{s}_t \leq 1/2] \leq 0.8$ for all tasks t. Let us define the constant $c = 0.8$.

Tasks in L^1 are succesfully scheduled if and only if their size is atmost 1. Hence

$$\begin{aligned}\mathbf{E}[\mathcal{P}_1(\mathcal{A}')] &= \sum_{t \in L^1} v_t \Pr[s_t \leq 1] \\ &= \sum_{t \in L^1} \tilde{v}_t\end{aligned}$$

Let F denote the value of the objective for the optimal integral solution to $\phi'(\mathbf{1})$. The set of tasks in L^1 is edge-disjoint since $f(1) = 1$ and hence

$$\mathbf{E}[\mathcal{P}_1(\mathcal{A}')] \leq F$$

For $i \geq 2$, a task t in L^i is succesfully scheduled only if its size is less than or equal to 1 and atleast $i-2$ of the $i-1$ tasks stacked below it on the most stacked-up edge (let us call it e) in P_t at the time of its scheduling are of size atmost 1/2. This is because if two of these $i-1$ tasks have size more than 1/2 then the remnant capacity of e will be 0 and task t will not be successfully scheduled. These two events are independent. If we use the union bound to upper bound the probability of the second event, we infer that Pr[Task t is successfully scheduled] $\leq \Pr[s_t \leq 1] \cdot \binom{i-1}{i-2} c^{i-2}$. Note that we used the fact that $\Pr[\tilde{s}_t \leq 1/2] = \Pr[s_t \leq 1/2] \leq c$ for all tasks $t \in T$, which was derived above. Hence

$$\begin{aligned}\mathbf{E}[\mathcal{P}_i(\mathcal{A}')] &\leq \sum_{t \in L_i} v_t \Pr[s_t \leq 1] \cdot \binom{i-1}{i-2} c^{i-2} \\ &= (i-1)c^{i-2} \cdot \sum_{t \in L^i} \tilde{v}_t\end{aligned}$$

We know that the tasks in L^i can be partitioned into atmost $f(i)$ edge-disjoint subsets. Hence

$$\mathbf{E}[\mathcal{P}_i(\mathcal{A}')] \leq (i-1)c^{i-2} \cdot f(i) \cdot F$$

We use these bounds to bound the payoff of $\mathcal{A}'$.

$$\begin{aligned}\mathbf{E}[\mathcal{P}(\mathcal{A}')] &= \sum_{i \geq 1} \mathbf{E}[\mathcal{P}_i(\mathcal{A}')] \\ &\leq F + \sum_{i \geq 2} \big((i-1)c^{i-2} \cdot f(i) \cdot F\big) \\ &= F + \sum_{i \geq 2} \big((i-1)c^{i-2} \cdot (k(i-1)+1) \cdot F\big) \\ &= F + F \cdot \sum_{i \geq 0} \big((i+1)c^i\big) + F \cdot k \sum_{i \geq 0} \big((i+1)^2 c^i\big) \\ &= F \cdot \big(1 + \frac{1}{(1-c)^2} + k(\frac{1}{(1-c)^2} + \frac{2c}{(1-c)^3})\big) \\ &= (225k + 26)F\end{aligned}$$

We have already seen that we can find an optimal integral solution $\mathbf{x}'$ to $\phi'(\mathbf{1})$ in time $O((m+n)2^k)$. Consider the set $A = \{t \in T | x'_i = 1\}$. The algorithm $\mathcal{A}$ schedules tasks in A in arbitrary order. The constrants of $\mathcal{L}'(\mathbf{1})$ are such that the tasks in A are edge-disjoint. Hence

$$\begin{aligned}\mathbf{E}[\mathcal{P}(\mathcal{A})] &= \sum_{t \in A} v_t \Pr[s_t \leq 1] \\ &= \sum_{t \in A} \tilde{v}_t \\ &= \sum_{t \in T} \tilde{v}_t x'_t \\ &= F\end{aligned}$$

We infer that for every non-adaptive algorithm $\mathcal{A}'$,

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{225k + 26} \cdot \mathbf{E}[\mathcal{P}(\mathcal{A}')]$$

Hence

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{225k + 26} \cdot OPT_N$$

Chapter 6

Approximation Algorithms

In this section, we combine the algorithms in §4 and §5 according to the strategy described in §3 to obtain non-adaptive polynomial-time approximation algorithms for the various special cases of sUfpTreeEdgeSubset that we are interested in.

Theorem 6.0.4 *There exists a non-adaptive polynomial-time algorithm $\mathcal{A}$ for the sRapPath for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{36} \cdot OPT$$

This implies that the adaptivity gap of sRapPath is atmost 36.

Proof. We know from Theorem 4.1.1, by choosing $p = 1/2$, that for positive $\delta < 1/2$ there exists an algorithm $\mathcal{A}_S(\delta)$ which for δ-small instances of sRapPath guarantees an expected payoff of at least $\phi(\mathbf{2}) \cdot (1 - 2\delta)/16 \geq OPT \cdot (1 - 2\delta)/16$. Theorem 5.1.2 implies that for δ-large instances of sRapPath, there exists an algorithm $A_L(\delta)$ which guarantees an expected payoff of at least $\phi(\mathbf{2}) \cdot \delta/2 \geq OPT \cdot \delta/2$. We infer from Theorem 3.0.2 that there exists an algorithm $\mathcal{A}$ for sRapPath which guarantees an expected payoff of at least $OPT \cdot 1/(16/(1-2\delta) + 2/\delta)$. This quantity attains its maximum value in the interval $(0, 1/2)$ at $\delta = 1/6$ which equals $OPT \cdot 1/36$. ∎

Theorem 6.0.5 *There exists a non-adaptive polynomial-time algorithm $\mathcal{A}$ for the sUfpPath under the NBA for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{6310.18} \cdot OPT$$

This implies that the adaptivity gap of the sUfpPath under the NBA is atmost 6310.18.

Proof. Consider $\delta = 0.0005$. We know from Theorem 4.2.2, that there exists an algorithm $\mathcal{A}_S$ which for δ-small instances of the sUfpPath under the NBA guarantees an expected payoff of at least $\phi(\mathbf{c} + \mathbf{1}) \cdot 1/310.18 \geq OPT \cdot 1/310.18$. Theorem 5.2.2 implies that for δ-large instances of the sUfpPath under the NBA, there exists an algorithm A_L which guarantees a payoff of at least $\phi'(\mathbf{1}) \cdot \delta/3 \geq OPT \cdot \delta/3$. We infer from Theorem 3.0.2 that there exists an algorithm $\mathcal{A}$ for the sUfpPath under the NBA which guarantees an expected payoff of at least $OPT \cdot 1/(310.18 + 3/\delta) = OPT \cdot 1/6310.18$. ∎

Theorem 6.0.6 *There exists a non-adaptive polynomial-time algorithm $\mathcal{A}$ for the sUfpTree under the NBA for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{25077.59} \cdot OPT$$

This implies that the adaptivity gap of sUfpTree *under the* NBA *is atmost* 25077.59*.*

Proof. Consider $\delta = 0.0005$. We know from Theorem 4.2.3, that there exists an algorithm $\mathcal{A}_S$ which for δ-small instances of the sUfpTree under the NBA guarantees an expected payoff of at least $\phi(\mathbf{c}+\mathbf{1}) \cdot 1/1077.59 \geq OPT \cdot 1/1077.59$. Theorem 5.2.4 implies that for δ-large instances of the sUfpTree under the NBA, there exists an algorithm A_L which guarantees a payoff of at least $\phi'(\mathbf{1}) \cdot \delta/12 \geq OPT \cdot \delta/12$. We infer from Theorem 3.0.2 that there exists an algorithm $\mathcal{A}$ for the sUfpTree under the NBA which guarantees an expected payoff of at least $OPT \cdot 1/(1077.59 + 12/\delta) = OPT \cdot 1/25077.59$. ∎

Theorem 6.0.7 *There exists a non-adaptive polynomial-time algorithm $\mathcal{A}$ for the* sRAPT-kS *for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{8(k^2+4k+1)} \cdot OPT$$

This implies that the adaptivity gap of sRAPT-kS *is atmost* $8(k^2+4k+1)$*.*

Proof. We know from Theorem 4.1.1, by choosing $p = 1/2$, that there exists an algorithm $\mathcal{A}_S(\delta)$ which for δ-small instances of sRAPT-kS guarantees an expected payoff of at least $\phi(2) \cdot (1 - 2\delta)/(4(k+1)^2) \geq OPT \cdot (1-2\delta)/(4(k+1)^2)$. Theorem 5.1.3 implies that for δ-large instances of sRAPT-kS, there exists an algorithm A_L which guarantees an expected payoff of at least $\phi'(\mathbf{1}) \cdot \delta/(4k) \geq OPT \cdot \delta/(4k)$. We infer from Theorem 3.0.2 that there exists an algorithm $\mathcal{A}$ for sRAPT-kS which guarantees an expected payoff of at least $OPT \cdot 1/(4k/\delta + 4(k+1)^2/(1-2\delta))$. At $\delta = 1/4$ this quantity equals $OPT \cdot 1/(8(k^2+4k+1))$. ∎

Theorem 6.0.8 *There exists a non-adaptive polynomial-time algorithm $\mathcal{A}$ for the* sUFPT-kS *under the* NBA *for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{822.37k^{2.15} + 12000k} \cdot OPT$$

This implies that the adaptivity gap of sUFPT-kS *under the* NBA *is atmost* $822.37k^{2.15} + 12000k$*.*

Proof. Consider $\delta = 0.0005$. We know from Theorem 4.2.1 that there exists an algorithm $\mathcal{A}_S$ which for δ-small instances of sUFPT-kS under the NBA guarantees an expected payoff of at least $\phi(\mathbf{c}+\mathbf{1}) \cdot 1/(822.37k^{2.15}) \geq OPT \cdot 1/(822.37k^{2.15})$. Theorem 5.2.4 implies that for δ-large instances of sUFPT-kS under the NBA, there exists an algorithm A_L which guarantees a payoff of at least $\phi'(\mathbf{c}+\mathbf{1}) \cdot \delta/(6k) \geq OPT \cdot \delta/(6k)$. We infer from Theorem 3.0.2 that there exists an algorithm $\mathcal{A}$ for sUFPT-kS under the NBA which guarantees an expected payoff of at least $OPT \cdot 1/(6k/\delta + 822.37k^{2.15}) = OPT \cdot 1/(12000k + 822.37k^{2.15})$ ∎

Theorem 6.0.9 *There exists a non-adaptive polynomial-time algorithm $\mathcal{A}$ for the* sRAPkT-T *for which*

$$\mathbf{E}[\mathcal{P}(\mathcal{A})] \geq \frac{1}{8k^2 + 241k + 34} \cdot OPT_N$$

Proof. We know from Theorem 4.1.1, by choosing $p = 1/2$, that there exists an algorithm $\mathcal{A}_S(\delta)$ which for δ-small instances of sRAPkT-T guarantees an expected payoff of at least $\phi(2) \cdot (1 - 2\delta)/(4(k+1)^2) \geq OPT_N \cdot (1-2\delta)/(4(k+1)^2)$. Theorem 5.3.3 implies that for δ-large instances of sRAPkT-T, there exists an algorithm A_L which guarantees an expected payoff of at least $OPT_N \cdot 1/(225k+16)$. We infer from Theorem 3.0.2 that there exists an algorithm $\mathcal{A}$ for sRAPkT-T which guarantees an expected payoff of at least $OPT \cdot 1/(225k + 26 + 4(k+1)^2/(1-2\delta))$. At $\delta = 1/4$, this quantity equals $OPT_N \cdot 1/(8k^2 + 241k + 34)$. ∎