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# Kolmogorov Approximation

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## 1 Introduction

Many different approaches to approximation of probability distributions are studied in the literature [10, 13, 14]. The papers vary in the types random variables involved, how they are represented, and in the criteria used for evaluation of the quality of the approximations. This paper is on approximating discrete distributions represented as explicit probability mass functions with ones that are simpler to store and to manipulate. This is needed, for example, when a discrete distribution is given as a large data-set, obtained, e.g., by sampling, and we want to represent it approximately with a small table.

The main contribution of this paper is an efficient algorithm for computing the best possible approximation of a given random variable with a random variable whose complexity is not above a prescribed threshold, where the measures of the quality of the approximation and the complexity of the random variable are as specified in the following two paragraphs.

We measure the quality of an approximation by the distance between the original variable and the approximate one. Specifically, we use the Kolmogorov distance which is one of the most used in statistical practice and literature. Given two random variables  $X$  and  $X'$  whose cumulative distribution functions (cdfs) are  $F_X$  and  $F_{X'}$ , respectively, the Kolmogorov distance between  $X$  and  $X'$  is  $d_K(X, X') = \sup_t |F_X(t) - F_{X'}(t)|$  (see, e.g., [9]). We say that  $X'$  is a good approximation of  $X$  if  $d_K(X, X')$  is small.

The complexity of a random variable is measured by the size of its support, the number of values that it can take,  $|\text{support}(X)| = |\{x: \Pr(X = x) \neq 0\}|$ . When distributions are maintained as explicit tables, as done in many implementations of statistical software, the size of the support of a variable is proportional to the amount of memory needed to store it and to the complexity of the computations around it.

In summary, the exact notion of optimality of the approximation targeted in this paper is:

**Definition 1.** A random variable  $X'$  is an optimal  $m$ -approximation of a random variable  $X$  if  $|\text{support}(X')| \leq m$  and there is no random variable  $X''$  such that  $|\text{support}(X'')| \leq m$  and  $d_K(X, X'') < d_K(X, X')$ .

The main contribution of the paper is a constructive proof of:

**Theorem 2.** Given a random variable  $X$  and a number  $m$ , there is an algorithm with memory and time complexity  $O(|\text{support}(X)|^2 \cdot m)$  that computes an optimal  $m$ -approximation of  $X$ .

31 The rest of the paper is organized as follows. In Section 2 we describe how our work relates to other  
 32 algorithms and problems studied in the literature. In Section 3 we detail the proposed algorithm,  
 33 analyze its properties, and prove Theorem 2. In Section 4 we demonstrate how the proposed approach  
 34 performs on the problem of estimating the probability of hitting deadlines is plans and compare it to  
 35 alternatives approximation approaches from the literature. We also demonstrate the performance of  
 36 our approximation algorithm on some randomly generated random variables. The paper is concluded  
 37 with a discussion in Section 5.

## 38 2 Related Work

39 The problem studied in this paper is related to the theory of Sparse Approximation (aka Sparse  
 40 Representation) that deals with sparse solutions for systems of linear equations, as follows.

Given a matrix  $D \in \mathbb{R}^{n \times p}$  and a vector  $x \in \mathbb{R}^n$ , the most studied sparse representation problem is finding the sparsest possible representation  $\alpha \in \mathbb{R}^p$  satisfying  $x = D\alpha$ :

$$\min_{\alpha \in \mathbb{R}^p} \|\alpha\|_0 \text{ subject to } x = D\alpha.$$

41 where  $\|\alpha\|_0 = |\{i : \alpha_i \neq 0, i = 1, \dots, p\}|$  is the  $\ell_0$  pseudo-norm, counting the number of non-zero  
 42 coordinates of  $\alpha$ . This problem is known to be NP-Hard with a reduction to NP-complete subset  
 43 selection problems.

In these terms, using also the  $\ell_\infty$  norm that represents the maximal coordinate and the  $\ell_1$  norm that represents the sum of the coordinates, our problem can be phrased as:

$$\min_{\alpha \in [0, \infty)^p} \|x - D\alpha\|_\infty \text{ subject to } \|\alpha\|_0 = m \text{ and } \|\alpha\|_1 = 1.$$

44 where  $D$  is the all-ones triangular matrix (the entry at row  $i$  and column  $j$  is one if  $i \leq j$  and zero  
 45 otherwise),  $x$  is related to  $X$  such that the  $i$ th coordinate of  $x$  is  $F_X(x_i)$  where  $\text{support}(X) =$   
 46  $\{x_1 < x_2 < \dots < x_n\}$  and  $\alpha$  is related to  $X'$  such that the  $i$ th coordinate of  $\alpha$  is  $f_{X'}(x_i)$ . The  
 47 functions  $F_X$  and  $f_{X'}$  represent, respectively, the cumulative distribution function of  $X$  and the  
 48 mass distribution function of  $X'$ . This, of course, means that the coordinates of  $x$  are assumed to be  
 49 positive and monotonically increasing and that the last coordinate of  $x$  must be one. We demonstrate  
 50 an application for this specific sparse representation problem and show that it can be solve in  $O(n^2m)$   
 51 time and memory.

## 52 3 An Algorithm for Optimal Approximation

53 [[DF: move somewhere to intro: Obviously every random variable with support of size of at most  $m$   
 54 serves as some approximation, the challenge is how to find an  $m$ -optimal approximation for  $X$ .]]  
 55 [[DF: move to intro: we call the distance between  $X$  and the  $m$ -optimal-approximation random  
 56 variable of  $X$ , the  $m$ -optimal distance from  $X$ . ]]

57 We next describe in details the proof of theorem 2.

58 In the following we set  $X$  as a random variable with a finite support of size  $n$ , and we set  $0 < m \leq n$ .  
 59 We need to find an  $m$ -optimal approximation random variable  $X'$ .

60 Our first step is to show that it is enough to limit our search to  $X'$ 's such that  $\text{support}(X') \subseteq$   
 61  $\text{support}(X)$ .

62 **Lemma 3.** *There is an  $m$ -optimal-approximation  $X'$  of  $X$  such that  $\text{support}(X') \subseteq \text{support}(X)$ .*

[DF: This proof is unclear to me, please clean. ] Assume for contradiction is a random variable  $X''$  with support size  $m$  such that  $d_K(X, X'')$  is minimal but  $\text{support}(X'') \not\subseteq \text{support}(X)$ . We will show how to transform  $X''$  support such that it will be contained in  $\text{support}(X)$ . Let  $v'$  be the first  $v' \in \text{support}(X'')$  and  $v' \notin \text{support}(X)$ . Let  $v = \max\{i : i < v' \wedge i \in \text{support}(X)\}$ . Every  $v'$  we will replace with  $v$  and name the new random variable  $X'$ , we will show that  $d_K(X, X'') = d_K(X, X')$ . First, note that:  $F_{X''}(v') = F_{X'}(v)$ ,  $F_X(v') = F_X(v)$ . Second,  $F_{X'}(v') - F_X(v') = F_{X'}(v) - F_X(v)$ . Therefore,  $d_K(X, X'') = d_K(X, X')$  and  $X'$  is also an optimal approximation of  $X$ .  $\square$

Next, note that every random variable  $X''$  with support of size at most  $m$  that is contained in  $\text{support}(X)$  be described by first setting the (at most  $m$ ) elements of the support of  $X''$ ; then for every such option, determine  $X''$  by setting probability values for the elements in the chosen support of  $X'$ , and setting 0 for rest of the elements.

Since from Lemma 3 we can assume wlog that if  $X'$  is an  $m$ -optimal approximation variable for  $X$  then  $\text{support}(X') \subseteq \text{support}(X)$ , our search to find such  $X'$  takes two steps. Denote the set of random variables with support  $S$  by  $\mathbb{X}_S$ . In step 1, we find the  $m$ -optimal approximation random variable among all random variables in  $\mathbb{X}_S$ , and denote the  $m$ -optimal distance for  $\mathbb{X}_S$  by  $\varepsilon(X, S)$ . Next, in Step 2, among all the possible supports we find the support setting  $S$  of size  $\leq m$  for which  $\varepsilon(X, S)$  is minimal: We describe an efficient way to do so.

### 3.1 Step 1

We first fix a set  $S \subseteq \text{support}(X)$  of size at most  $m$ , and among all the random variables in  $\mathbb{X}_S$  find one with a minimal distance from  $X$ . To that, set  $S = \{x_1 < \dots < x_m\} \subseteq \text{support}(X)$ . To simplify the proofs set  $x_0 = -\infty$ , and  $x_{m+1} = \infty$ . Then  $x_0 < x_1$  and  $x_m < x_{m+1}$ . In addition recall that for every random variable  $X''$   $F_{X''}(-\infty) = 0$  and  $F_{X''}(\infty) = 1$ . For the rest of this section we assume  $S$  is fixed and therefore is not necessarily included in the notation.

Next, as the elements of  $S$  are also elements of  $\text{support}(X)$ , we can define the following weight function that we use to find the  $m$ -optimal distance  $\varepsilon(X, S)$ .

**Definition 4.** For  $0 \leq i < m$  let

$$w(x_i, x_{i+1}) = \begin{cases} P(x_i < X < x_{i+1}) & \text{if } i = 0 \text{ or } i = m; \\ P(x_i < X < x_{i+1})/2 & \text{otherwise.} \end{cases}$$

Note that when  $i = 0$  (resp.  $i = m + 1$ ) then  $x_i = -\infty$  (resp.  $x_i = \infty$ ).

Finally define:

$$\varepsilon(X, S) = \max_{i=0, \dots, m} w(x_i, x_{i+1}) \quad (1)$$

We first show that  $\varepsilon(X, S)$  is a lower bound. That is, every random variable in  $\mathbb{X}_S$  has a distance at least  $\varepsilon(X, S)$ . Then, we present a random variable  $X' \in \mathbb{X}_S$  with distance  $\varepsilon(X, S)$ . It then follows that such  $X'$  is an  $m$ -optimal approximation random variable among all random variables in  $\mathbb{X}_S$ .

The intuition behind choosing these specific weights and  $\varepsilon(X, S)$  being a lower bound is as follows. For every  $1 \leq i \leq m$  let  $\hat{x}_i$  be the maximal element of  $\text{support}(X)$  that is smaller than  $x_i$ . Then since for every  $X' \in \mathbb{X}_S$  the probability values of  $X'$  for the elements not in  $S$  are set to 0, we

98 have that  $F_{X'}(\hat{x}_{i+1}) = F_{X'}(x_i)$ . Therefore the distance between  $X'$  and  $X$  at points  $x_i$  and  $\hat{x}_{i+1}$  is  
 99 increased by  $F_X(\hat{x}_{i+1}) - F_X(x_i) = P(x_i < X < x_{i+1})$ .

100 Formally we have the following.

101 **Proposition 5.** *For every random variable  $X'$  with  $\text{support}(X') = S$  we have  $d_k(X, X') \geq$   
 102  $\varepsilon(X, S)$ .*

103 *Proof.* Let  $X'$  be a random variable with support  $S$ . Then by definition, for every  $0 \leq i \leq m$ ,  
 104  $d_k(X, X') \geq \max\{|F_X(x_i) - F_{X'}(x_i)|, |F_X(\hat{x}_{i+1}) - F_{X'}(\hat{x}_{i+1})|\}$ . Note that  $F_{X'}(x_i) = F_{X'}(\hat{x}_{i+1})$   
 105 since the probability value for all the elements not in  $S$  is set to 0.

106 If  $i = 0$ , that is  $x_i = -\infty$ , we have that  $F_X(x_i) = F_{X'}(x_i) = F_{X'}(\hat{x}_{i+1}) = 0$  and therefore  
 107  $d_k(X, X') \geq |F_X(\hat{x}_{i+1}) - F_{X'}(\hat{x}_{i+1})| = |F_X(\hat{x}_{i+1}) - F_X(x_i)| = P(x_i < X < x_{i+1}) = w(x_i, x_{i+1})$ .

108 If  $i = m$ , that is  $x_{i+1} = \infty$ , note that  $F_X(\hat{x}_{i+1}) = F_{X'}(\hat{x}_{i+1}) = 1$ . Therefore  $F_{X'}(x_i) = 1$  as well.  
 109 Therefore  $d_k(X, X') \geq |F_X(\hat{x}_i) - F_{X'}(\hat{x}_i)| = |F_X(\hat{x}_{i+1}) - F_X(x_i)| = P(x_i < X < x_{i+1}) = w(x_i, x_{i+1})$ .  
 110 [[DF: fix]]

111 Otherwise for every  $1 \leq i < m$ , we use the fact that  $\max\{|a|, |b|\} \geq |a - b|/2$  for every  $a, b \in \mathfrak{R}$ , to  
 112 have  $d_k(X, X') \geq \max\{|F_X(x_i) - F_{X'}(x_i)|, |F_X(\hat{x}_{i+1}) - F_{X'}(\hat{x}_{i+1})|\}$ , and therefore  $d_k(X, X') \geq$   
 113  $1/2|F_X(x_i) - F_X(\hat{x}_{i+1}) + F_{X'}(\hat{x}_{i+1}) - F_{X'}(x_i)|$ . Since it is given that  $F_{X'}(\hat{x}_{i+1}) - F_{X'}(x_i) =$   
 114  $P(x_i < X' < x_{i+1}) = 0$ , we have that  $d_k(X, X') \geq 1/2|F_X(x_i) - F_X(\hat{x}_{i+1})| = P(x_1 < X <$   
 115  $x_2)/2 = w(x_i, x_{i+1})$ .

116 We saw that  $d_k(X, X') \geq w(x_i, x_{i+1})$  for every  $0 \leq i \leq m$ . Therefore by definition of  $\varepsilon(X, S)$ ,  
 117 proof follows.  $\square$

118 [[DF: here I stopped]]

119 **Definition 6.** Let  $X'$  to be  $f_{X'}(x_i) = w(x_{i-1}, x_i) + w(x_i, x_{i+1}) + f_X(x_i)$  for  $i = 1, \dots, m$  and  
 120  $f_{X'}(x) = 0$  for  $x \notin S$ .

121 **Lemma 7.** For  $i > 1$ , if  $F_{X'}(x_i) - F_X(x_i) = w(x_i, x_{i+1})$  then  $F_{X'}(x_{i+1}) - F_X(x_{i+1}) =$   
 122  $w(x_{i+1}, x_{i+2})$ .

*Proof.*

$$F_{X'}(x_{i+1}) - F_X(x_{i+1}) = \quad (2)$$

$$\begin{aligned} &= f_{X'}(x_{i+1}) - f_X(x_{i+1}) - P(X < x_{i+1}) + P(X' < x_{i+1}) \\ &= f_{X'}(x_{i+1}) - f_X(x_{i+1}) - F_X(x_i) - P(x_i < X < x_{i+1}) + F_{X'}(x_i) \\ &= f_{X'}(x_{i+1}) - f_X(x_{i+1}) - F_X(x_i) - 2w(x_i, x_{i+1}) + F_{X'}(x_i) \end{aligned} \quad (3)$$

$$= f_{X'}(x_{i+1}) - f_X(x_{i+1}) - 2w(x_i, x_{i+1}) + w(x_i, x_{i+1}) \quad (4)$$

$$= w(x_i, x_{i+1}) + w(x_{i+1}, x_{i+2}) - 2w(x_i, x_{i+1}) + w(x_i, x_{i+1}) \quad (5)$$

$$= w(x_{i+1}, x_{i+2})$$

123 By Definition 4 the probability  $P(x_{i-1} < X < x_i) = 2w(x_{i-1}, x_i)$  as in Equation (3). Equation (4)  
 124 is deduced by the induction hypothesis and Equation (5) where  $f_{X'}(x_i) - f_X(x_i) = w(x_{i-1}, x_i) +$   
 125  $w(x_i, x_{i+1})$  is true by construction, see Definition 6.  $\square$

126 **Lemma 8.** Base case:  $i = 1, F_{X'}(x_1) - F_X(x_1) = w(x_1, x_2)$ .

*Proof.*

$$\begin{aligned}
F_{X'}(x_1) - F_X(x_1) &= \\
&= f_{X'}(x_1) - f_X(x_1) - w(x_0, x_1) \\
&= w(x_0, x_1) + w(x_1, x_2) - w(x_0, x_1) \\
&= w(x_1, x_2)
\end{aligned}$$

127

□

128 **Proposition 9.** *There exists  $X'$  such that  $\text{support}(X') = S$  and  $d_k(X, X') = \varepsilon(X, S)$ .*

### 129 3.2 Step 2

130 Chakravarty, Orlin, and Rothblum [2] proposed a polynomial-time method that, given a certain  
 131 objective functions (additive), finds an optimal consecutive partition. Their method involves the  
 132 construction of a graph such that the (consecutive) set partitioning problem is reduced to the problem  
 133 of finding the shortest path in that graph.

134 The KolmogorovApprox algorithm (Algorithm 1) starts by constructing a directed weighted graph  
 135  $G$  similar to the method of Chakravarty, Orlin, and Rothblum [2]. The nodes  $V$  consist of the  
 136 support of  $X$  together with an extra two nodes,  $-\infty$  and  $\infty$  for technical reasons, whereas the  
 137 edges  $E$  connect every pair of nodes in one direction (lines 1-2). The weight  $w$  of each edge  
 138  $e = (x, y) \in E$  is determined by one of two cases as in Definition 4. The first is where nodes  
 139  $x$  or  $y$  are the source or target nodes respectively. In this case, the weight is the probability of  $X$   
 140 to get a value between  $x$  and  $y$ , non inclusive, i.e.,  $w(e) = \Pr(x < X < y)$ . The second case  
 141 is where  $x$  and  $y$  are not a source or target nodes, here the weight is the probability of  $X$  to get a  
 142 value between  $x$  and  $y$ , non inclusive, divided by two i.e.,  $w(e) = \Pr(x < X < y)/2$ . The values  
 143 taken are non inclusive, since we are interested only in the error value. The source node of the  
 144 shortest path problem at hand corresponds to the  $-\infty$  node added to  $G$  in the construction phase,  
 145 and the target node is the extra node  $\infty$ . The set of all solution paths in  $G$ , i.e., those starting at  
 146  $-\infty$  and ending in  $\infty$  with at most  $m$  edges, is called  $\text{paths}(G, -\infty, \infty)$ . The goal is to find the  
 147 path  $l$  in  $\text{paths}(G, -\infty, \infty)$  with the lightest bottleneck (line 3). This can be achieved by using the  
 148 *Bellman – Ford* algorithm with two tweaks. The first is to iterate the graph  $G$  in order to find only  
 149 paths with length of at most  $m$  edges. The second is to find the lightest bottleneck as opposed to  
 150 the traditional objective of finding the shortest path. This is performed by modifying the manner of  
 151 “relaxation” to  $\text{bottleneck}(x) = \min[\max(\text{bottleneck}(v), w(e))]$ , done also in [15]. Consequently,  
 152 we find the lightest maximal edge in a path of length  $\leq m$ , which represents the minimal error,  
 153  $\varepsilon(X, S)$ , defined in Definition ?? where the nodes in path  $l$  represent the elements in set  $S$ . The  
 154 approximated random variable  $X'$  is then derived from the resulting path  $l$  (lines 4-5). Every node  
 155  $x \in l$  represent a value in the new calculated random variable  $X'$ , we then iterate the path  $l$  to find  
 156 the probability of the event  $f_{X'}(x)$  as described in Definition 6. For every edge  $(x_i, x_j) \in l$  we  
 157 determine: if  $(x_i, x_j)$  is the first edge in the path  $l$  (i.e.  $x_i = -\infty$ ), then node  $x_j$  gets the full weight  
 158  $w(x_i, x_j)$  and it's own weight in  $X$  such that  $f_{X'}(x_j) = f_X(x_j) + w(x_i, x_j)$ . If  $(x_i, x_j)$  is not the  
 159 first nor the last edge in path  $l$  then we divide it's weight between nodes  $x_i$  and  $x_j$  in addition to their  
 160 own original weight in  $X$  and the probability that already accumulated. If  $(x_i, x_j)$  is the last edge  
 161 in the path  $l$  (i.e.  $x_j = \infty$ ) then node  $x_i$  gets the full weight  $w(x_i, x_j)$  in addition to what was already  
 162 accumulated such that  $f_{X'}(x_j) = f_{X'}(x_i) + w(x_i, x_j)$ .

163 **Theorem 10.** *KolmogorovApprox( $X, m$ ) is an  $m$ -optimal-approximation of  $X$ .*

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**Algorithm 1:** KolmogorovApprox( $X, m$ )

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```
1  $S = \text{support}(X) \cup \{\infty, -\infty\}$ 
2  $G = (V, E) = (S, \{(x, y) : x < y\})$ 
3  $(x_0, \dots, x_{m+1}) = l = \text{argmin}_{l \in \text{paths}(G, -\infty, \infty), |l| \leq m} \max\{w(e) : e \in l\}$ 
4 for  $0 < i < m + 1$  do
5    $f_{X'}(x_i) = w(x_{i-1}, x_i) + w(x_i, x_{i+1}) + f_X(x_i)$ 
6 return  $X'$ 
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164 **Theorem 11.** *The KolmogorovApprox( $X, m$ ) algorithm runs in time  $O(mn^2)$ , using  $O(n^2)$  mem-*  
165 *ory where  $n = |\text{support}(X)|$ .*

166 *Proof.* Constructing the graph  $G$  takes  $O(n^2)$ . The number of edges is  $O(E) \approx O(n^2)$  and for every  
167 edge the weight is at most the sum of all probabilities between the source node  $-\infty$  and the target  
168 node  $\infty$ , which can be done efficiently by aggregating the weights of already calculated edges. The  
169 construction is also the only stage that requires memory allocation, specifically  $O(E + V) = O(n^2)$ .  
170 Finding the shortest path takes  $O(m(E + V)) \approx O(mn^2)$ . Since  $G$  is DAG (directed acyclic graph)  
171 finding shortest path takes  $O(E + V)$ . We only need to find paths of length  $\leq m$ , which takes  
172  $O(m(E + V))$ . Deriving the new random variable  $X'$  from the computed path  $l$  takes  $O(mn)$ . For  
173 every node in  $l$  (at most  $m$  nodes), calculating the probability  $P(s < X < \infty)$  takes at most  $n$ .  
174 To conclude, the worst case run-time complexity is  $O(n^2 + mn^2 + mn) = O(mn^2)$  and memory  
175 complexity is  $O(E + V) = O(n^2)$ .  $\square$

## 176 4 A case study and experimental results

177 The case study examined in our experiments is the problem of task trees with deadlines [4, 3].  
178 Hierarchical planning is a well-established field in AI [6, 7, 8], and is still relevant nowadays [1, 16].  
179 A hierarchical plan is a method for representing problems of automated planning in which the  
180 dependency among tasks can be given in the form of networks, here we focus on hierarchical plans  
181 represented by task trees. The leaves in a task tree are *primitive* actions (or tasks), and the internal  
182 nodes are either *sequence* or *parallel* actions. The plans we deal with are of stochastic nature, where  
183 the duration of a primitive action is given by a random variable.

184 A sequence node denotes a series of tasks that should be performed consecutively, whereas a parallel  
185 node denotes a set of tasks that begin at the same time. A *valid* plan is one that is fulfilled before some  
186 given *deadline*, i.e., its *makespan* is less than or equal to the deadline. The objective in this context  
187 is to compute the probability that a given plan is valid, or more formally computing  $P(X < T)$ ,  
188 where  $X$  is a random variable representing the makespan of the plan and  $T$  is the deadline. As said  
189 above, resource consumption (task duration) is uncertain, and described as probability distributions  
190 in the leaf nodes. We assume that the distributions are independent but *not* necessarily identically  
191 distributed and that the random variables are discrete and have a finite support.

192 The problem of finding the probability that a task tree satisfies a deadline is known to be NP-hard. In  
193 fact, even the problem of summing a set of random variables is NP-hard [11]. This is an example of  
194 an explicitly given random variable that we need to estimate deadline meeting probabilities for.

195 In the first experiment we focus on is the problem of task trees with deadlines, and consider three  
196 types of task trees. The first type includes logistic problems of transporting packages by trucks and  
197 airplanes (from IPC2 <http://ipc.icaps-conference.org/>). Hierarchical plans of those logistic problems

198 were generated by the JSHOP2 planner [12] (see example problem, Figure 1, one parallel node with  
 199 all descendant task nodes being in sequence). The second type consists of task trees used as execution  
 200 plans for the ROBIL team entry in the DARPA robotics challenge (DRC simulation phase), and the  
 201 third type is of linear plans (sequential task trees). The primitive tasks in all the trees are modeled as  
 202 discrete random variables with support of size  $M$  obtained by discretization of uniform distributions  
 over various intervals. The number of tasks in a tree is denoted by  $N$ .

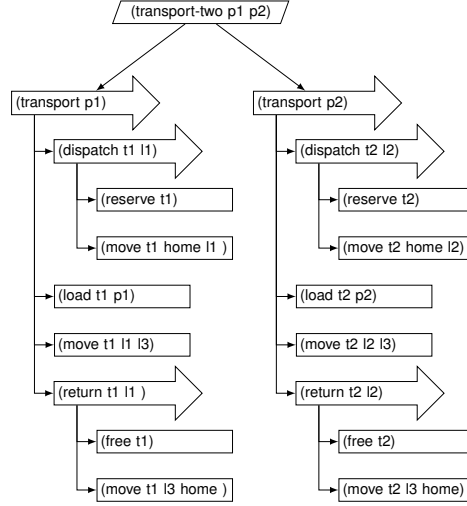


Figure 1: A plan generated by the JSHOP2 algorithm. Arrow shapes represent sequence nodes, parallelograms represent parallel nodes, and rectangles represent primitive nodes.

203

204 We implemented the approximation algorithm for solving the deadline problem with four different  
 205 methods of approximation. The first two are for achieving a one-sided Kolmogorov approximation –  
 206 the OptTrim [3] and the Trim [4] operators, and the third is a simple sampling scheme. We used those  
 207 methods as a comparison to the Kolmogorov approximation with the suggested KolmogorovApprox  
 208 algorithm. The parameter  $m$  of OptTrim and KolmogorovApprox corresponds to the inverse of  $\varepsilon$   
 209 given to the Trim operator. Note that in order to obtain some error  $\varepsilon$ , one must take into consideration  
 210 the size of the task tree  $N$ , therefore,  $m/N = 1/(\varepsilon \cdot N)$ . We ran also an exact computation as  
 211 a reference to the approximated one in order to calculate the error. The experiments conducted  
 212 with the following operators and their parameters: KolmogorovApprox operator with  $m = 10 \cdot N$ ,  
 213 the OptTrim operator with  $m = 10 \cdot N$ , the Trim as operator with  $\varepsilon = 0.1/N$ , and two simple  
 simulations, with a different samples number  $s = 10^4$  and  $s = 10^6$ .

Task Tree	$M$	KolmogorovApprox	OptTrim	Trim	Sampling	
		$m/N=10$	$m/N=10$	$\varepsilon \cdot N=0.1$	$s=10^4$	$s=10^6$
Logistics ( $N=34$ )	2	0	0	0.0019	0.007	0.0009
	4	0	0.0046	0.0068	0.0057	0.0005
Logistics ( $N=45$ )	2	0.0002	0.0005	0.002	0.015	0.001
	4	0	0.003	0.004	0.008	0.0006
DRC-Drive ( $N=47$ )	2	0	0.004	0.009	0.0072	0.0009
	4	0	0.008	0.019	0.0075	0.0011
Sequential ( $N=10$ )	2	0.009	0.015	0.024	0	0
	4	0.001	0.024	0.04	0.008	0.0016
	10	0	0.028	0.06	0.0117	0.001

Table 1: Comparison of estimated errors with respect to the reference exact computation on various task trees.

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Table 1 shows the results of the main experiment. The quality of the solutions provided by using the OptTrim operator are better (lower errors) than those provided by the Trim operator, following the optimality guarantees, but is interesting to see that the quality gaps happen in practice in each of the examined task trees. However, in some of the task trees the sampling method produced better results than the approximation algorithm with OptTrim. Nevertheless, the approximation algorithm comes with an inherent advantage of providing an exact quality guarantees, as opposed to the probabilistic guarantees provided by sampling.

In order to better understand the quality gaps in practice between KolmogorovApprox, OptTrim, and Trim, we investigate their relative errors when applied on single random variables with support size  $n = 100$ , and different support sizes of the resulting random variable approximation ( $m$ ). In each instance of this experiment, a random variable is randomly generated by choosing the probabilities of each element in the support from a uniform distribution and then normalizing these probabilities so that they sum to one.

Figure 2 present the error produced by the above methods. The depicted results are averages over several instances (50 instances) of random variables. The curves in the figure show the average error of OptTrim and Trim operators with comparison to the average error of the optimal approximation provided by KolmogorovApprox as a function of  $m$ .

According to the depicted results it is evident that increasing the support size of the approximation  $m$  reduces the error, as expected, in all three methods. However, errors produced by the KolmogorovApprox are significantly smaller, safe to say, a half of the error produced by OptTrim and Trim, it is clear both in the table (the relative error is mostly above 1) and in the graph.

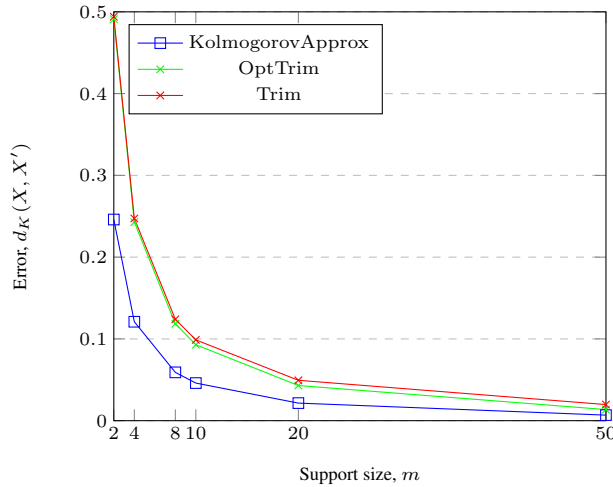


Figure 2: Error comparison between KolmogorovApprox, OptTrim, and Trim, on randomly generated random variables as function of  $m$ .

We also examined how our algorithm compares to linear programming as described and discussed, for example, in [13]. We ran an experiment to compare the run-time between the KolmogorovApprox algorithm with the run-time of a state-of-art implementation of linear programming. We used the “Minimize” function of Wolfram Mathematica and fed it with the equations  $\min_{\alpha \in \mathbb{R}^n} \|x - \alpha\|_\infty$  subject to  $\|\alpha\|_0 \leq m$  and  $\|\alpha\|_1 = 1$ . The run-time comparison results were clear and persuasive, for a random variable with support size  $n = 10$  and  $m = 5$ , the LP algorithm run-time was 850 seconds, where the KolmogorovApprox algorithm run-time was less than a tenth of a second. For  $n = 100$  and  $m = 5$ , the KolmogorovApprox algorithm run-time was 0.14 seconds and the LP



algorithm took more than a day. Due to these timing results of the LP algorithm we did not proceed to examine it any further. Since it is not trivial to formally analyze the run-time of the LP algorithm, we conclude by the reported experiment that in this case the LP algorithm might not be as efficient as KolmogorovApprox algorithm whose complexity is proven to be polynomial in Theorem 11.

## 5 Discussion

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