

Tight Approximation Algorithms for Ordered Covering

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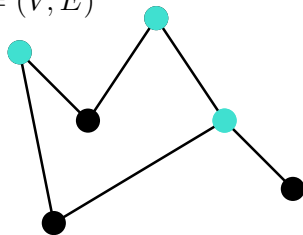
2023

Minimum Vertex Cover

Definition

Given a graph $G = (V, E)$, find the smallest cardinality subset $S \subseteq V$ such that for all edges e in E , $e \cap S \neq \emptyset$.

$G = (V, E)$



■ Vertex Cover

Figure: Vertex Cover in G

Alternate View (Scheduling)

1. One Machine.
2. The vertices are the jobs.

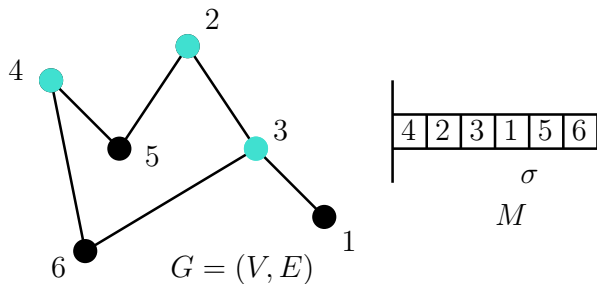


Figure: Scheduling Vertices on a Machine

Objective Function?

Alternate View (Scheduling): Cover Times

Definition

Given a graph $G = (V, E)$ and a schedule $\sigma : V \rightarrow [n]$ of its vertices, the cover time of an edge is the first moment a vertex in the edge is scheduled.

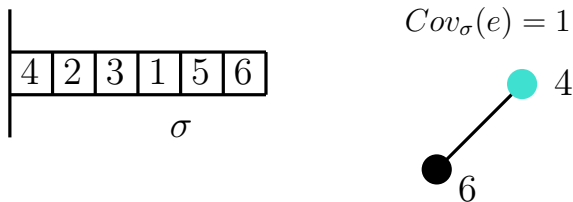


Figure: Cover Time of an Edge

1. Vertex Cover: $\min_\sigma \max_{e \in E} Cov_\sigma(e)$.
2. Min-Sum Vertex Cover: $\min_\sigma \sum_{e \in E} Cov_\sigma(e)$
[FLT04, BBFT21, Sta22]

Can we unify?

Ordered Optimization [AS, CSa, BSS18, CSb, CS19]

Given a schedule σ , arrange e in descending order as:

$$\text{Cov}_\sigma(e_1) \geq \text{Cov}_\sigma(e_2) \geq \dots \text{Cov}_\sigma(e_m).$$

$$\min_\sigma \text{Cov}_\sigma(e_1)$$

$$\min_\sigma \sum_{j=1}^m \text{Cov}_\sigma(e_j)$$

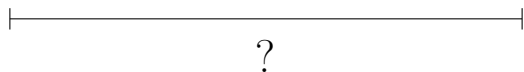


Figure: Generalized Objective Functions

Ordered Optimization [AS, CSa, BSS18, CSb, CS19]

Given a schedule σ , arrange e in descending order as:

$$\text{Cov}_\sigma(e_1) \geq \text{Cov}_\sigma(e_2) \geq \dots \text{Cov}_\sigma(e_m).$$

$$\begin{array}{ccc} \min_\sigma \text{Cov}_\sigma(e_1) & & \min_\sigma \sum_{j=1}^m \text{Cov}_\sigma(e_j) \\ & \underbrace{\hspace{10em}}_{\ell} & \\ & \min_\sigma \sum_{j=1}^{\ell} \text{Cov}_\sigma(e_j) & \end{array}$$

Figure: Top- ℓ Objective Functions

Ordered Objective Functions:

$$\min_\sigma \sum_{j=1}^m w_j \text{Cov}_\sigma(e_j)$$

for $w_1 \geq w_2 \geq \dots w_m \geq 0$. This framework has gained a lot of attention for clustering (Ordered k -Median) and Load Balancing problems.

Our Contribution



Figure: One Ring to Rule Them All

Current State

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- ▶ Vertex Cover

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 - ▶ Upper Bound: 2-approx (Folklore)
 - ▶ Hardness of Approximation: $(2 - \epsilon)$ under UGC [KR08].

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- ▶ Ordered Min-Sum Vertex Cover
 - ▶ Upper Bound: 8-approx [GGKT08] (All-norm, more general result).
 - ▶ Lower Bound: $(2 - \epsilon)$ under UGC (Captures VC).

However, the techniques for upper bounds are very different across the problems.

Current State

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- ▶ Set Cover
 - ▶ Upper Bound: $O(\log n)$ -approx [Joh73, Sla96].
 - ▶ Lower Bound: NP-Hard to approximate within $(1 - \varepsilon) \log_e n$ [DS14]

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 - ▶ Upper Bound: 4-approx [FLT04].
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- ▶ Ordered Set Cover
 - ▶ $O(\log n)$ -approx. [GGKT08] Upper Bound (Much more general result, All-norm) s
 - ▶ General Lower Bound: NP-Hard to approximate within $\Omega(\log n)$ (Captures Set Cover). But for specialised Top- ℓ objectives?

Our Results

Definition

Ordered Min-Sum Vertex Cover(OMSVC): Let $G = (V, E)$ be a graph, and a $w_1 \geq w_2 \geq \dots w_m \geq 0$ be a sequence of non-negative weights. Design a schedule σ of vertices to minimize $\sum_j w_j \text{Cov}_\sigma(e_j)$ where e_j is the ordering of edges in descending order of cover times.

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Theorem

There is a $(2 + \varepsilon)$ -approximation algorithm for OMSVC running in time $n^{O(1/\varepsilon)}$.

Our Results

Definition

Top- ℓ Set Cover: Let E be a set and \mathcal{I} be a collection of subsets of E . Design a schedule σ of sets to minimize $\sum_{j=1}^{\ell} \text{Cov}_{\sigma}(e_j)$ for a fixed $\ell \in [n]$ where the elements e_j are ordered in descending order of cover times.

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The natural greedy algorithm gives a $(8 \log_2(n/\ell) + 16)$ -approx for Top- ℓ Set Cover.

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It is hard to approximate the Top- ℓ Set Cover problem within a factor better than $\max(\Omega(1), \Omega(\log(n/\ell)))$.

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It is hard to approximate the Top- ℓ Set Cover problem within a factor better than $\max(\Omega(1), \Omega(\log(n/\ell)))$.

First ℓ -based approximation ratio and hardness result for Top- ℓ objectives (to our knowledge).

Overview of the Talk

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- ▶ We will give a review of the approach of Feige et. al. [FLT04] and why it fails in our problem.
- ▶ We will show how a *dependent-rounding*[GKPS06] based approach fixes these problems.

Reduction

Let $\sigma : V \rightarrow T$ be a schedule for an instance of Top- ℓ Vertex Cover.

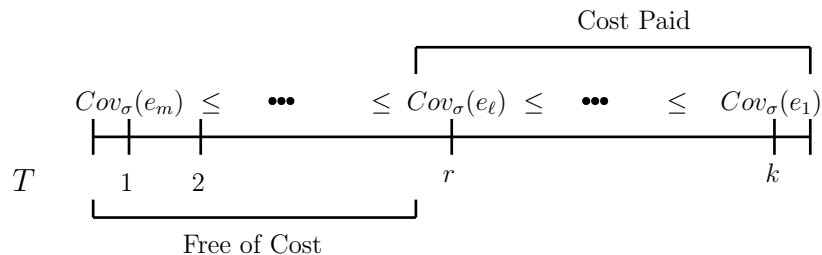


Figure: Top- ℓ Vertex Cover

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Reduction

Intuition

- ▶ Try to write down an ILP for this problem.
- ▶ Any schedule should be encoded as a feasible solution to this ILP.
- ▶ ILP should know edges which have the Top- ℓ cover times for any schedule σ .
- ▶ How to write constraints for this?

Problem? Do not know the ordering before hand.

Reduction

Shift by a Discount

Add the Discount back later

$$(Cov_{\sigma}(e_m) - \lambda)_+ \leq \dots \leq (Cov_{\sigma}(e_{\ell}) - \lambda)_+ \leq \dots \leq (Cov_{\sigma}(e_1) - \lambda)_+$$

$$\forall \lambda \geq 0 \quad \underbrace{\sum_{e \in E} (Cov_{\sigma}(e) - \lambda)_+}_{\text{Oblivious to Ordering}} + \underbrace{\lambda \cdot \ell}_{\text{Fixed}} \geq \sum_{i=1}^{\ell} Cov_{\sigma}(e_i)$$

Figure: Top- ℓ Vertex Cover

Reduction

Shift by Good Discount

Add the Discount back later

$$\lambda = \text{Cov}_{\sigma^*}(e_\ell)$$

$$(Cov_{\sigma^*}(e_m) - \lambda)_+ \leq \dots \leq (Cov_{\sigma^*}(e_\ell) - \lambda)_+ \leq \dots \leq (Cov_{\sigma^*}(e_1) - \lambda)_+$$

$$\underbrace{\sum_{e \in E} (Cov_{\sigma^*}(e) - \lambda)_+}_{\text{Oblivious to Ordering}} + \underbrace{\lambda \cdot \ell}_{\text{Fixed}} = \sum_{i=1}^{\ell} Cov_{\sigma^*}(e_i)$$

Figure: Top- ℓ Vertex Cover

Reduction

Try to minimize:

$$\sum_{e \in E} (\text{Cov}_{\sigma}(e) - \lambda)_+$$

over all possible schedules for a correct guess
 $\lambda = \text{Cov}_{\sigma^*}(e_{\ell})$.

Reduction

Theorem

[AS, BSS18, CSa, CS19, CSb] Let σ^* be the optimal schedule to an instance of Top- ℓ Vertex Cover. Then, a schedule σ satisfying:

$$\sum_{e \in E} (\text{Cov}_{\sigma} - 2\lambda)_+ \leq 2 \sum_{e \in E} (\text{Cov}_{\sigma^*} - \lambda)_+$$

implies that $\sum_{j=1}^{\ell} \text{Cov}_{\sigma}(e_j) \leq 2 \sum_{j=1}^{\ell} \text{Cov}_{\sigma^*}(e_j)$.

Definition

Discounted Min-Sum Vertex Cover (DMSVC) Let $G = (V, E)$ be a graph, and a $\lambda \geq 0$ be a discount. Design a schedule σ of vertices which satisfies:

$$\sum_{e \in E} (\text{Cov}_{\sigma} - 2\lambda)_+ \leq 2 \sum_{e \in E} (\text{Cov}_{\sigma^*} - \lambda)_+$$

Plan for the Talk

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1. In the following, we will try to solve the Discounted Min-Sum Vertex Cover problem via an LP-rounding algorithm.

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2. Let us first try to write down the linear program.

Intuition for Linear Program

Variables: $x_{v,t}$, $u_{e,t}$.

Indicator variables.

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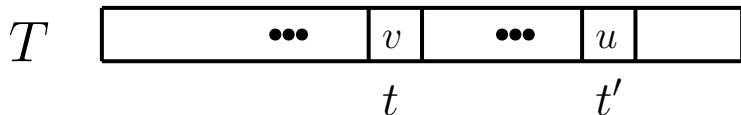
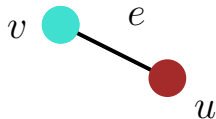
$$x_{v,t} = \begin{cases} 1 & v \text{ is scheduled at } t \\ 0 & \text{otherwise} \end{cases}$$

$$u_{e,t} = \begin{cases} 1 & \text{Cov}_\sigma(e) \geq t \\ 0 & \text{otherwise} \end{cases} .$$

$u_{e,t}$ tracks at each step if e has not been covered.

Intuition For Linear Program

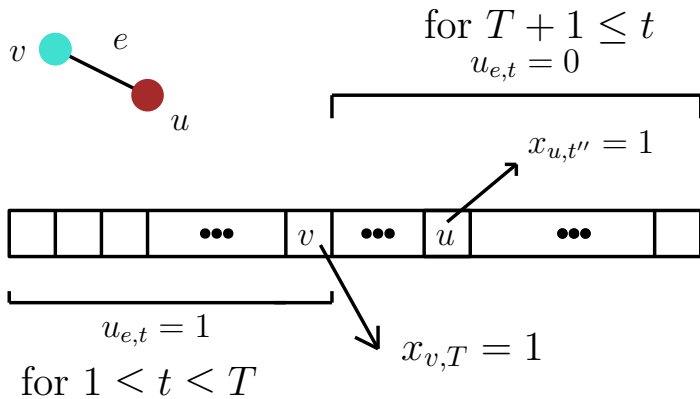
Variables: $u_{e,t}, x_{v,t}$



$$\textcircled{1} \quad \sum_{v' \in V} x_{v',t} \leq 1$$

Figure: Intuition for variables and constraints

Intuition For Linear Program



$$\textcircled{2} \quad u_{e,t} + \sum_{t' < t} x_{v,t'} + \sum_{t' < t} x_{u,t'} \geq 1$$

Figure: Intuition for variables and constraints, $\text{Cov}_\sigma(e) = \sum_t u_{e,t}$

Intuition For Linear Program

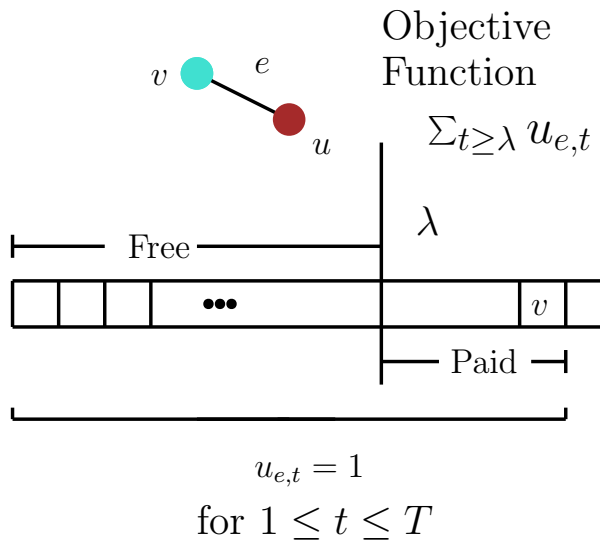


Figure: Intuition for variables and constraints

DMSVC Linear Program

$$\text{Minimize } \sum_{t \geq \lambda} \sum_{e \in E} u_{e,t}, \quad s.t.$$

$$\sum_{v \in V} x_{v,t} \leq 1, \quad \forall t = 1, 2, \dots \quad (1)$$

$$u_{e,t} + \sum_{t' < t} x_{u,t'} + \sum_{t' < t} x_{v,t'} \geq 1, \quad \forall e = (u, v), t = 1, 2, \dots \quad (2)$$

$$u, x \geq 0.$$

Bi-criteria algorithm for DMSVC

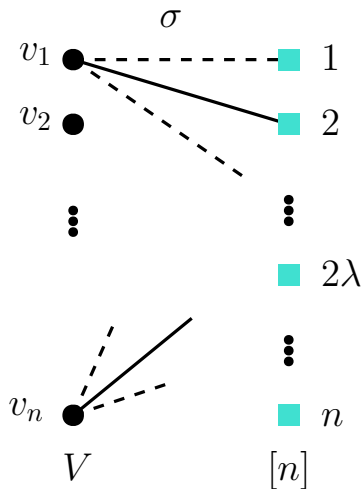


Figure: Assignment Graph

Naive Approach

Solve the above LP.

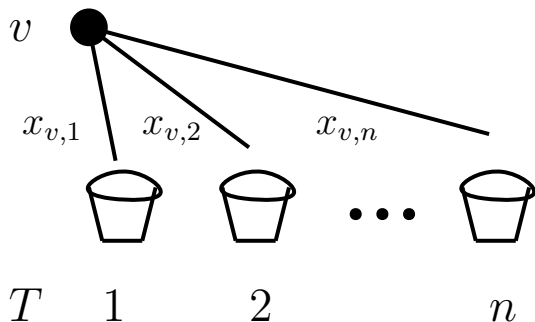


Figure: Try to throw each vertex in bins with probability $x_{v,t}$

Naive Approach

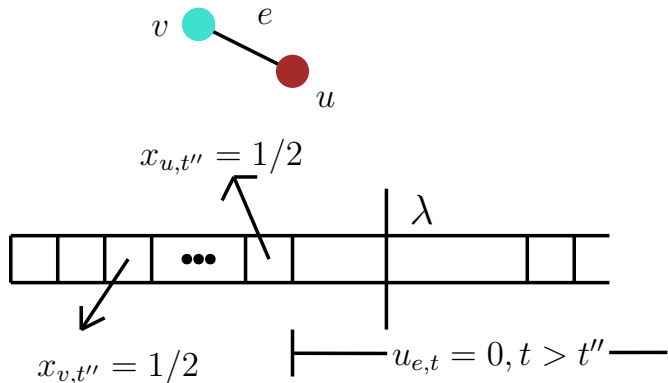


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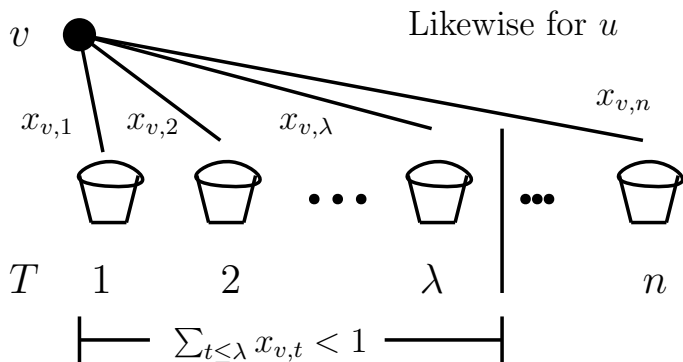


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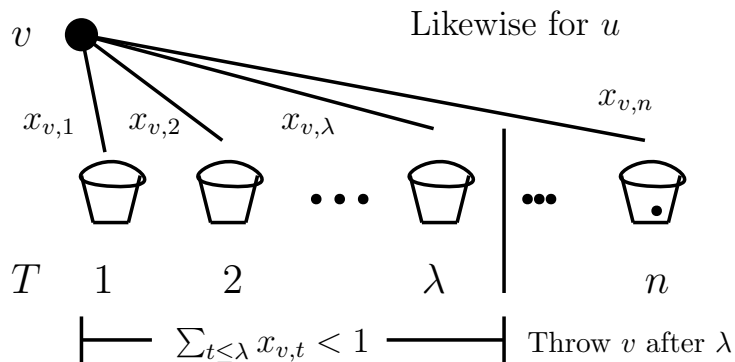


Figure: Ball might be thrown in the last bin

Naive Approach

Independently throw each vertex into the bins using scaled probabilities (x).

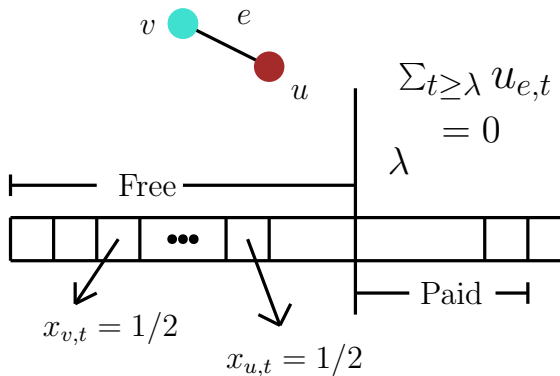


Figure: Linear Program does not pay anything, While we pay a lot.

Approach of [FLT04]

If $e = \{v, u\}$ is fractionally scheduled before λ , then either

$\sum_{t < \lambda} x_{v,t} \geq 1/2$ or $\sum_{t < \lambda} x_{u,t} \geq 1/2$.

(Since fractional covering means $\sum_{t < \lambda} x_{v,t} + \sum_{t < \lambda} x_{u,t} \geq 1$.)

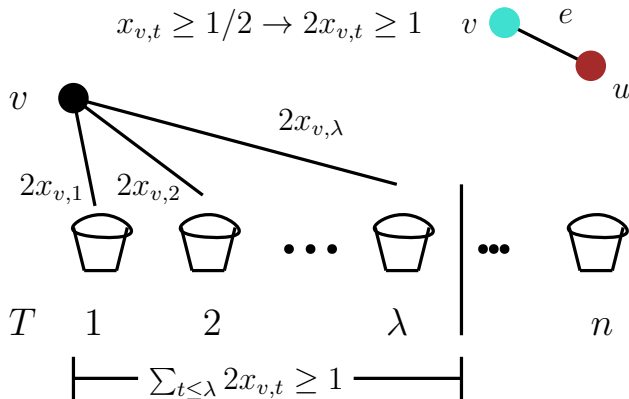


Figure: [FLT04]

Approach of [FLT04]

Independently throw each vertex into the bins using scaled probabilities ($2x$).

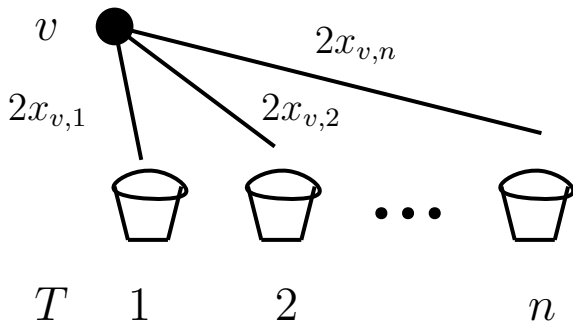


Figure: [FLT04]

Approach of [FLT04]

Break the bins and schedule a uniformly random permutation of vertices inside the bin.

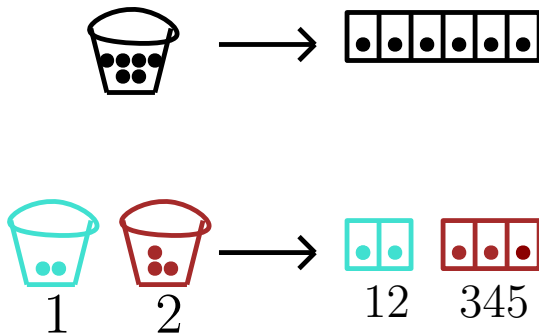


Figure: [FLT04]

Problem?

Recall, $\sum_{v \in V} x_{v,t} \leq 1$. Thus

$$\mathbb{E}[\text{\#vertices in a bin}] = 2 \sum_{v \in V} x_{v,t} \leq 2.$$

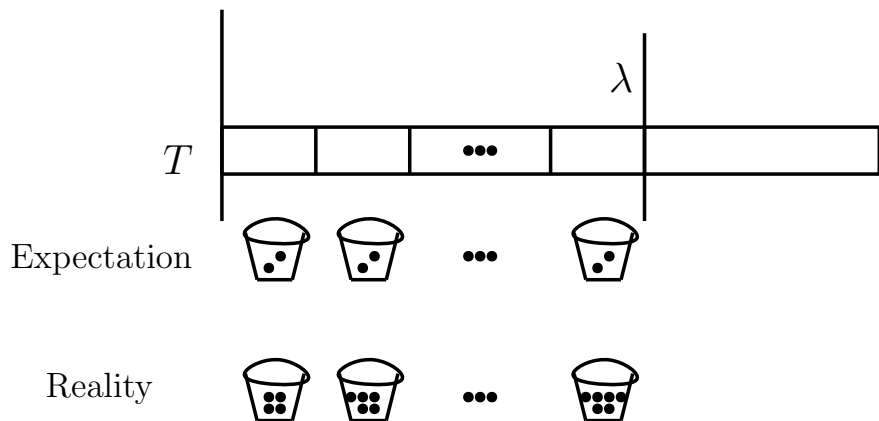


Figure: [FLT04]

Problem?

Want to ensure with high probability that at most 2λ vertices are scheduled within first λ slots.

Ingredients We Need

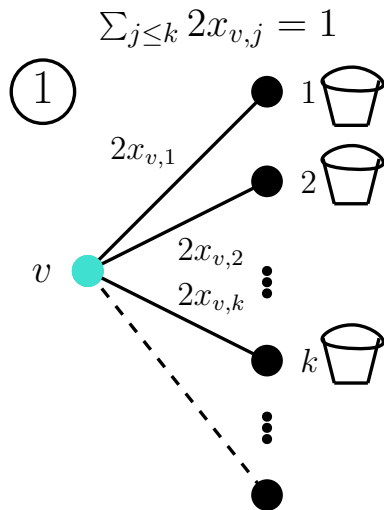


Figure: Marginal Preservation: Throw v into a bin with probability $2x_{v,t}$

Ingredients We Hope for

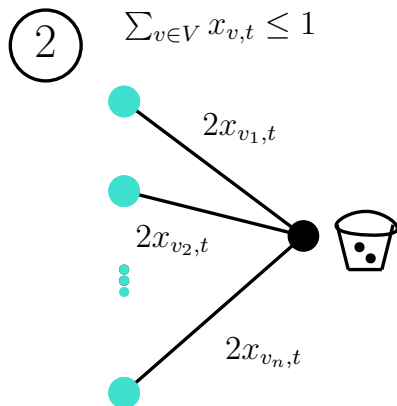


Figure: Dependent Rounding on Side of Slots

- ▶ ≤ 2 vertices in each bin with probability 1.
- ▶ Thus, $\leq 2\lambda$ vertices in first λ bins with probability 1.

Fix?



Dependent Rounding.

Dependent Rounding [GKPS06]

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Theorem

Given a weighted bipartite graph $(V \cup T, F, z : F \rightarrow [0, 1])$ ($z = 2x$), it is possible to sample a subset of edges $S \subseteq F$ satisfying the following criterion:

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2. $\deg_S(t) = \left\lceil \sum_{e \in \delta(t)} 2x_{v,t} \right\rceil \leq 2$ (Ensures that the load is at most 2).

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3. $\deg_S(v) = \sum_{e \in \delta(v)} 2x_{v,t} = 1$ (Ensures each vertex is thrown into exactly 1 bin)

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1. $\Pr((v, t) \in S) = 2x_{v,t}$ (Marginal Preservation),
2. $\deg_S(t) = \left[\sum_{e \in \delta(t)} 2x_{v,t} \right] \leq 2$ (Ensures that the load is at most 2).
3. $\deg_S(v) = \sum_{e \in \delta(v)} 2x_{v,t} = 1$ (Ensures each vertex is thrown into exactly 1 bin)
4. (Negative Correlation): For any time t ,
 $\Pr((v, t) \in S, (u, t) \in S) \leq \Pr((v, t) \in S) \Pr((u, t) \in S)$.
[However, we do not use it]

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3. Run Dependent rounding on the bipartite graph $(V \cup T, F, 2x : F \rightarrow [0, 1])$. (The sampled edges give an assignment of vertices to time slot).
4. Break bins of time slots t (Each bin has at most 2 vertices: cost goes up by at most 2).

The End

Thank you.

Open Directions





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- ▶ Getting a 2-approx. for All-Norm Vertex Cover (Improving from 8 [GGKT08])

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- ▶ Getting a 2-approx. for All-Norm Vertex Cover (Improving from 8 [GGKT08])
- ▶ Getting ℓ -dependent or w -dependent approximation algorithms for other problems (such as Load Balancing or k -Median).

References

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Interpolating between k-median and k-center: Approximation