# Approximation algorithm for minimum $\lambda$-edge-connected $k$-subgraph with metric costs 

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$(k, \lambda)$-subgraph problem:

- Input: Given a weighted undirected graph $G$ and integer parameters $k$ and $\lambda$
- Output: Find a minimum weight $\lambda$-edge-connected subgraph of $G$ containing at least $k$ nodes.
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Generalizes many classical problems:
- k-MST $\equiv(k, 1)$-subgraph problem. Approximation factor: $\sqrt{k}[13], O\left(\log ^{2} k\right)[1], O(\log n)$ [12], constant [3, 8] and 2 [9].
- min-cost $\lambda$-edge-connected spanning graph $\equiv(|V(G)|, \lambda)$-subgraph problem
( $k, \lambda$ )-subgraph problem in general graphs:
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- For arbitrary $\lambda$ : as hard as the $k$-densest subgraph problem [11]; best known approximation factor is $O\left(n^{\frac{1}{3}-\epsilon}\right)$ for some $\epsilon>0$.
- Chekuri and Korula [5]: $O\left(\log ^{2} n\right)$-approx for ( $k, 2$ )-subgraph problem with node-connectivity constraint.
- Here we consider the instances in which the underlying graph $G$ is metric:
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- Note that the constant factor approximation algorithms for $k$-MST and $k$-TSP are on graphs with metric cost function.
- The constant in the $O(1)$ term is between 400-500.
- Our algorithm is inspired by the work of Cheriyan and Vetta [4] for subset-node-connectivity problem.

We use two basic lower bounds on the optimum solution. Let $G^{*}$ be the optimal solution and OPT $=c\left(G^{*}\right) ; T^{*}$ be a MST of $G^{*}$.

## Observation

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## 1. Minimum Spanning Tree of $G^{*}$

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2. $\lambda$ nearest neighbors
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Our algorithm presents a solution whose cost is bounded within an $O(1)$-factor of these two bounds.

## General steps

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- In Phase 1 , we obtain a $(k-\lambda / 7, \lambda)$-subgraph, call it $H$, which has cost $O$ (OPT).
- In Phase 2, we show how to expand $H$ to a $(k, \lambda)$-subgraph, while keeping the cost within $O$ (Opt).

- Create a new graph $G^{\prime}\left(V \cup V^{\prime}, E^{\prime}\right)$ from $G$ by creating a new vertex $u^{\prime}$ for each $u \in G$ and $E^{\prime}=E \cup\left\{u u^{\prime} \mid u \in V\right\}$, $c\left(u u^{\prime}\right)=s_{u}$.


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- For every other edge in $G^{\prime}$ multiply its weight by $\lambda$.
- Using a $\rho$-approx alg, say ST-alg, for $k$-Steiner tree, find a $k$-Steiner tree $T^{\prime}$ in $G^{\prime}$ on terminal set $V^{\prime}$.

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- Using a $\rho$-approx alg, say ST-alg, for $k$-Steiner tree, find a $k$-Steiner tree $T^{\prime}$ in $G^{\prime}$ on terminal set $V^{\prime}$.
- Note that $T^{\prime}$ minimizes (approximately) $\sum_{u \in T^{\prime}} s_{u}+\lambda \sum_{e \in T^{\prime}} c_{e}$, and has at least $k$ nodes of $G$.

- Using the two lower bounds mentioned, it is easy to show that: Claim: $c\left(T^{\prime}\right)=4 \rho$ OPT.
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- For every $(u, v) \in T_{0}$ put a matching between the vertices in $S_{u}-S_{v}$ and $S_{v}-S_{u}$ to obtain $\lambda$-edge-connectivity.


## Algorithm for Phase 1

More details on how to do it...

- Let $v_{1}, \ldots, v_{k}$ be an ordering of vertices of $T_{0}$ s.t.

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- We call the set $S_{v_{i}}$ the ball with center $v_{i}$ and $B_{v_{i}} \subseteq S_{v_{i}}$, called the core, is the set of nodes with distance at most $2 s_{v_{i}} / \lambda$ to $v_{i}$.

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- Let $i^{*}$ be the smallest index such that $U_{i^{*}}=\bigcup_{\text {active } v_{j}, j \leq i *} S_{v_{j}}$ has at least $k-\lambda / 7$ nodes. We discard vertices $v_{j}$ with $j>i^{*}$.

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- Let $i^{*}$ be the smallest index such that $U_{i^{*}}=\bigcup_{\text {active } v_{j}, j \leq i *} S_{v_{j}}$ has at least $k-\lambda / 7$ nodes. We discard vertices $v_{j}$ with $j>i^{*}$. Note that $k-\frac{\lambda}{7} \leq\left|U_{i^{*}}\right| \leq k+\frac{6 \lambda}{7}$.


## Algorithm for Phase 1


(1) By short-cutting over non-active nodes in $T_{0}$, we obtain tree $T_{1}$. Then for each active nodes $v_{j} \in U_{i *}$ make a clique on $S_{v_{j}}$.

Algorithm for Phase 1

- Other vertices
$\bigcirc$ active nodes without balls $\quad \backsim$ matching edges
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(2) For every $(u, v) \in T_{1}$ put a matching between the vertices in $S_{u}-S_{v}$ and $S_{v}-S_{u}$ to obtain $\lambda$-edge-connectivity.
(3) It can be shown that the resulting graph $H$ is $\lambda$-edge-connected, has at least $k-\lambda / 7$ nodes and has cost at most $28 \rho$ OPT.


## Phase 2:

How to expand $H$ to have size $k$.
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## Case 1

If there is a set $A \subseteq G \backslash H$ of $k-|H|$ vertices s.t. has a low-cost matching between $A$ and $H$ then we can augment $H$ with small cost.

Two ways to augment $H$ to size $k$ in Phase 2

## Phase 2:

How to expand $H$ to have size $k$.
$\forall u \in G \backslash H$ : let $d(u, H)$ be the distance between $u$ and $H$.

## Case 1

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- connect each $u_{i}$ to $S_{M\left(u_{i}\right)}$ to obtain $\lambda$-edge-connectivity. Total cost added: $\lambda c(M)+2 c(H)$
- Show if $\left|G^{*} \backslash H\right| \leq \lambda / 3$, then this can be done with
$c(M) \leq \frac{6 \mathrm{OPT}}{\lambda}$


## Case 2

If there is a vertex $u \in G \backslash H$ s.t. $s_{u}+d(u, H)$ is small and $S_{u}$ contains at least $\lambda / 7$ vertices in $G \backslash H$ then we can augment $H$ with small cost.


- It can be shown that if $\left|G^{*} \backslash H\right|>\lambda / 3$, i.e. Case 1 does not happen, then this happens
- The cost of augmenting $H$ in this case is $\leq 12 \mathrm{OPT}+3 c(H)$.


## Conclusion

- So we can extend $H$ to a $(k, \lambda)$-subgraph by spending a total of at most $12 \mathrm{OPT}+3 c(H)$.
- Recalling that $c(H)=O(\mathrm{OPT})$, the total approximation ratio is $18+108 \rho$ with $\rho \leq 4$ being the ratio for $k$-Steiner tree.
- Getting a small constant factor approximation seems challenging, for general values of $\lambda$.
- For general cost functions, even for the special case of $\lambda=3$, there is no known non-trivial approximation algorithm or lower bound.
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