

Feedback Vertex Set Problem: Part 2

Vahan Mkrтчyаn

Lane Department of Computer Science and Electrical Engineering
West Virginia University

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Remark

Let $F = \{v_1, \dots, v_f\}$ be a feedback set, then $\text{cyc}(G) = \sum_{i=1}^f \delta_{G_{i-1}}(v_i) \leq \sum_{v \in F} \delta_G(v)$,
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If w is cyclomatic, and F is an optimal feedback set, then $c \cdot \text{cyc}(G) \leq c \cdot \sum_{v \in F} \delta_G(v) = w(F) = OPT$, hence $c \cdot \text{cyc}(G)$ is a lower bound for OPT .

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2-approximation algorithm for cyclomatic case

If w is cyclomatic, and F is a minimal feedback set, then $w(F) = c \cdot \sum_{v \in F} \delta_G(v) \leq 2 \cdot c \cdot \text{cyc}(G) \leq 2 \cdot OPT$.

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If w is cyclomatic, and F is a minimal feedback set, then $w(F) = c \cdot \sum_{v \in F} \delta_G(v) \leq 2 \cdot c \cdot \text{cyc}(G) \leq 2 \cdot OPT$. Hence a minimal feedback set approximates the optimal solution within a factor of 2 in case of cyclomatic weights.

Largest Cyclomatic and Residual Weight Functions

For a graph $G = (V, E)$ and a weight function w , let $c = \min_{v \in V} \left\{ \frac{w(v)}{\delta_G(v)} \right\}$.

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 $w'(v) = w(v) - t(v)$ is called the residual weight function.

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Decomposing into nested sequence of graphs and Cyclomatic Weight Functions

Repeated application of the above construction will result into a nested sequence $G_k \subset \dots \subset G_1 \subset G_0 = G$ of induced subgraphs of G (where G_k is acyclic), and a largest cyclomatic weight function t_i defined on G_i ($i = 0, \dots, (k - 1)$).

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Since the weight of a vertex v has been decomposed into the weights t_0, t_1, \dots, t_k , we have $\sum_{i:v \in V(G_i)} t_i(v) = w(v)$.

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Formulation of the algorithm

- For the input graph $G = (V, E)$ and a weight function w defined on it, construct the nested sequence $G_k \subset \dots \subset G_1 \subset G_0 = G$ of induced subgraphs of G (where G_k is acyclic), and a largest cyclomatic weight function t_i defined on G_i ($i = 1, \dots, k$) defined above.

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- return $F = F_0$.

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$$OPT = w(F^*) = \sum_{i=0}^k t_i(F^* \cap V(G_i)) \geq \sum_{i=0}^k OPT_i.$$

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$$w(F_0) = \sum_{i=0}^k t_i(F_0 \cap V(G_i)) = \sum_{i=0}^k t_i(F_i) \leq 2 \cdot \sum_{i=0}^k OPT_i \leq 2 \cdot OPT. \quad \square$$