

Partially Optimal Cubic Subspace Clustering

Research Project Machine Learning

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Partial Optimality for Cubic Clique Partition Problem

Extended cost function $c: \binom{S}{3} \cup \binom{S}{2} \cup \emptyset \rightarrow \mathbb{R}$

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Apply partial optimality conditions → solve subproblems

Partial Optimality Algorithm

Partial Optimality Algorithm:

Input: clustering y without fixed labels

while condition applied **do**

 apply subproblem-CUT-condition exhaustively

 apply one of JOIN-conditions (in effective order)

end while

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Output: partially optimal clustering y with some fixed labels

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Reduction to subproblems:

- 1 Subproblem-CUT-condition: fix CUT labels for element pairs from different sample subsets; solve each subset as an independent problem and accumulate the results in c_\emptyset ;
- 2 JOIN-Conditions: fix JOIN labels for elements of the sample subset; add the join-cost to c_\emptyset ; solve the problem where the subset is considered as one sample;

Subproblem-CUT and JOIN-Subset

Subproblem-CUT: cut sample subsets R_1, R_2, \dots, R_k that are only connected via non-negative costs (applied if $k > 1$)

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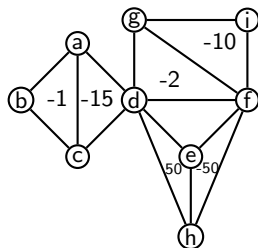
(Finding the worst bipartition joining cost can be reduced to the Min-Cut-Problem and solved as its dual Max-Flow-Problem)

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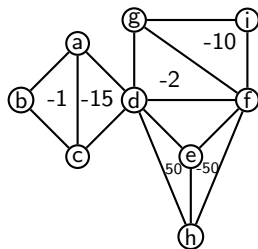
$$c_{\emptyset} = 0$$

Subproblem-CUT and JOIN-Subset

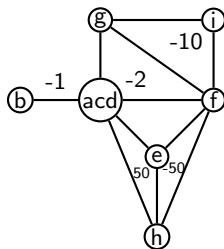
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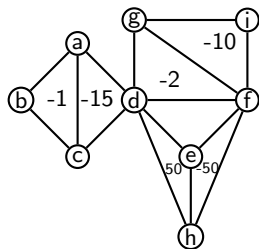
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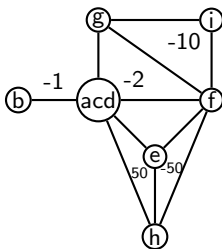
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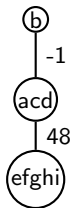
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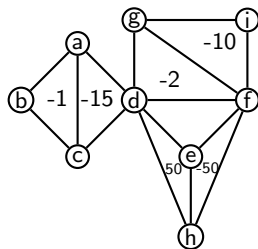
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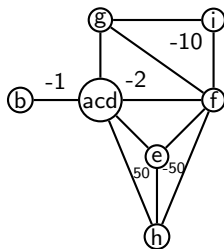
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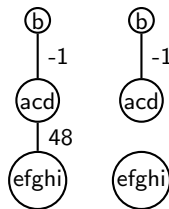
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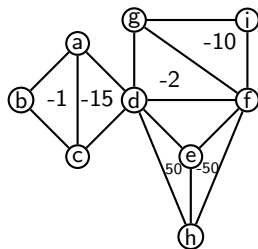
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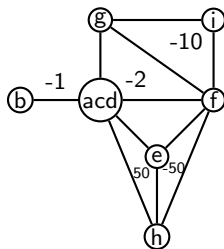
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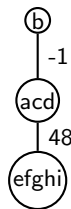
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Other JOIN-conditions and CUT-conditions

Overview of the other join-conditions (with pictures) Overview of the cut-conditions (with pictures) Pyramid example (solvable and unsolvable)

TODO

Class Diagram Algorithm implementation in ClusteringProblem

Features: ClusteringProblem is generally defined for all types of Cubic Clique Partition Problem (not necessarily points), cost function + sparse costs!, label computation, cut triples, logs joins and cuts! (add screenshots)