

# Fast Maximum Common Subgraph Search: A Redundancy-Reduced Backtracking Approach

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## Background: Maximum Common Subgraph Search

### Graph Isomorphism

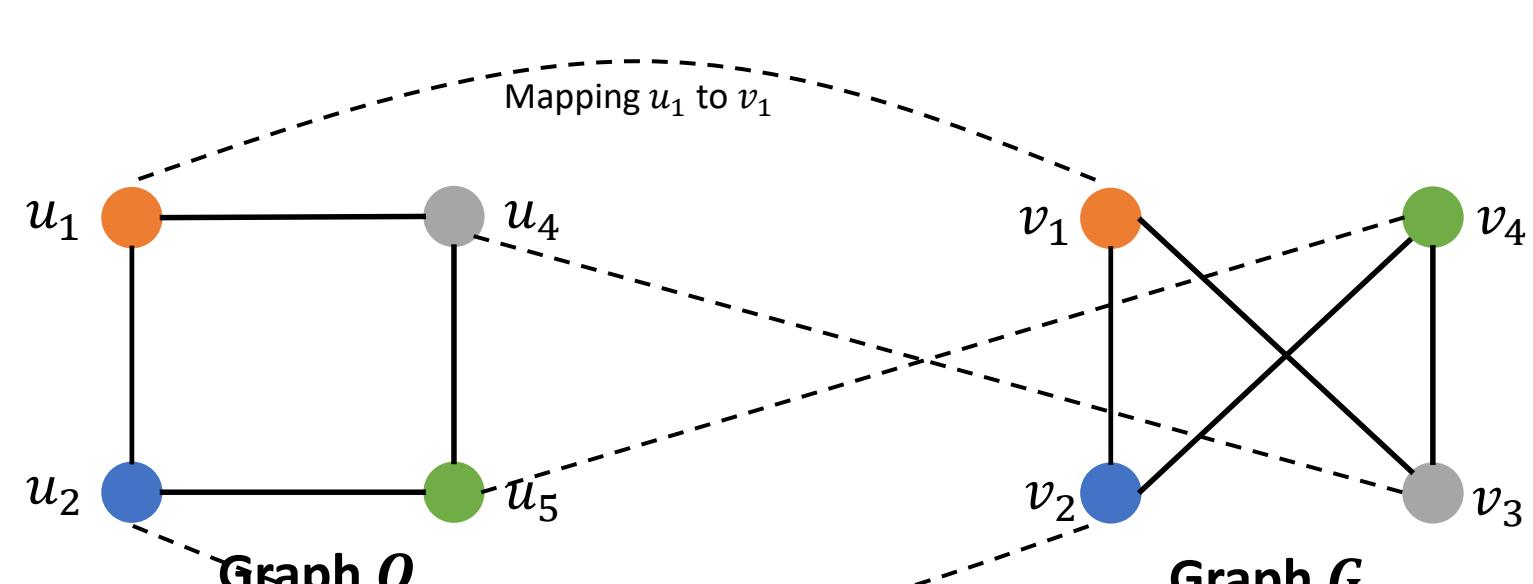


Figure 1.  $Q$  is isomorphic to  $G$  under bijection  $\phi: u_1 \rightarrow v_1, u_2 \rightarrow v_2, u_3 \rightarrow v_4, u_4 \rightarrow v_3, u_5 \rightarrow v_5, u_6 \rightarrow v_6, u_7 \rightarrow v_7$

### Common Induced Subgraph

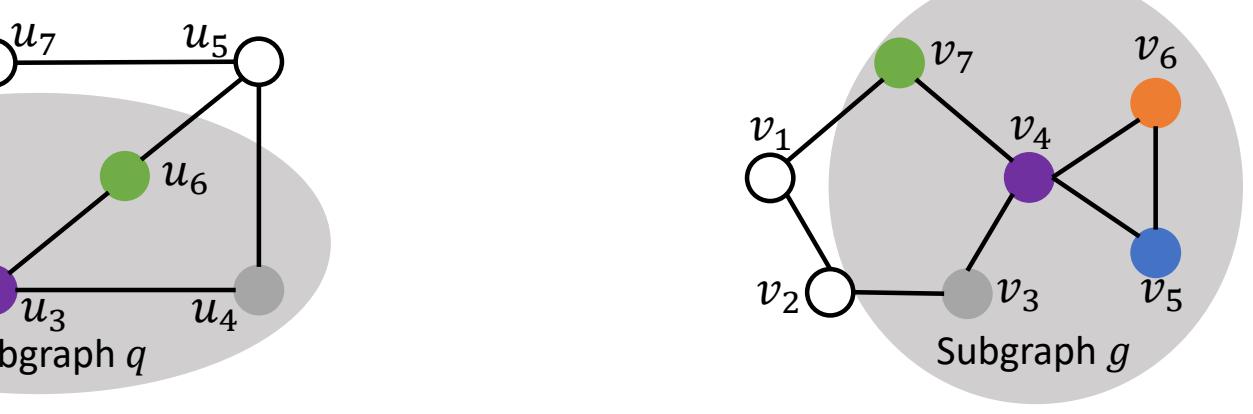


Figure 2. Common subgraph  $\langle q, g, \phi \rangle$  where  $q$  is isomorphic to  $g$  under bijection  $\phi$

### Maximum Common Subgraph (MCS) Search

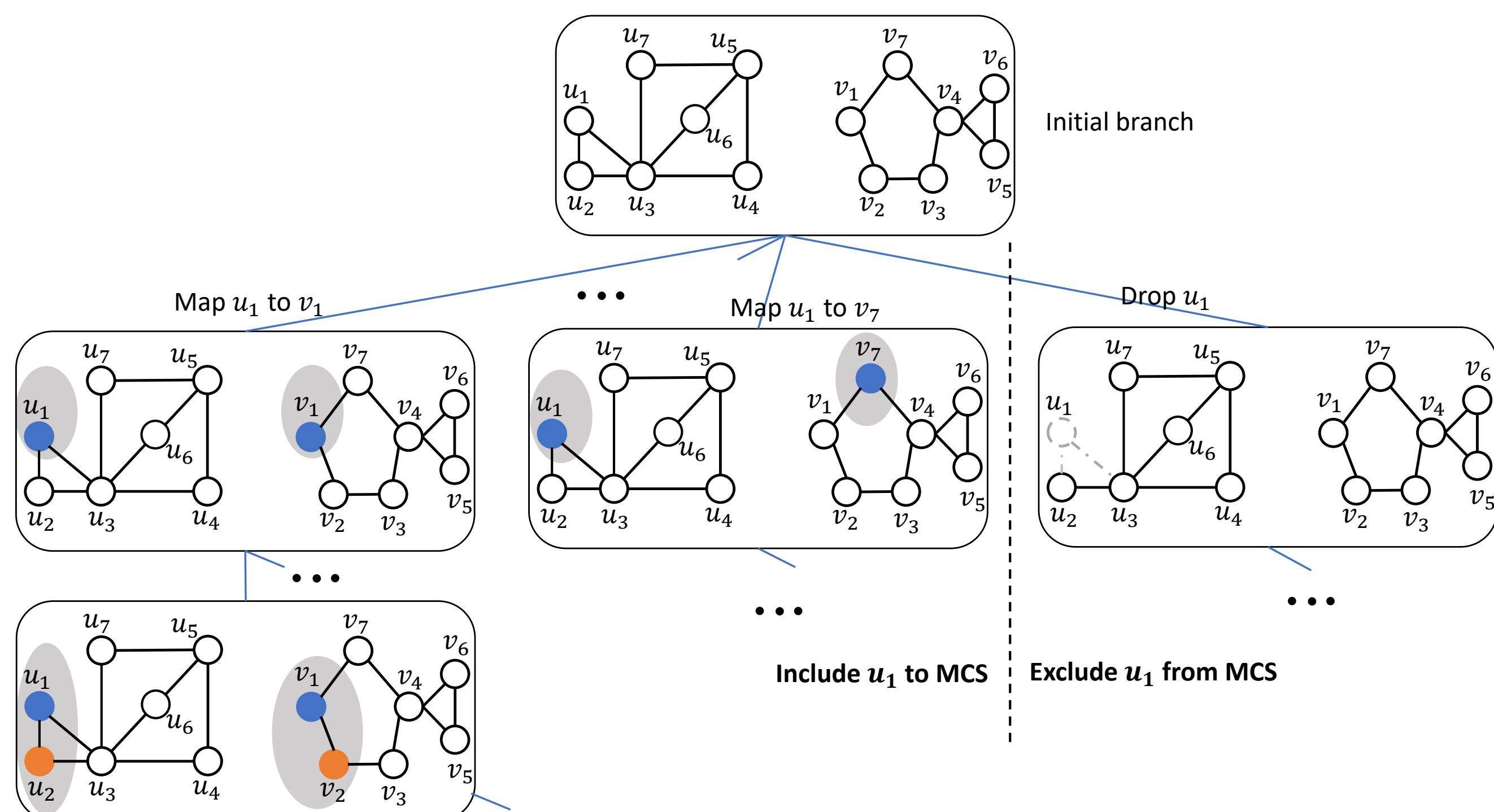
**Input:** two graphs  $Q = (V_Q, E_Q)$  and  $G = (V_G, E_G)$ .

**Output:** the common subgraph of  $Q$  and  $G$  with the largest number of vertices.

### Applications: Drug discovery, cheminformatics and etc.

### State-of-the-art backtracking method: McSplit [2, 1]

Main idea: recursively expand a partial solution via **backtracking** process.



### Our Algorithm: RRSplit

RRSPLIT follows the above backtracking process and adopts two types of reduction methods, namely **vertex-equivalence-based reduction** and **maximality-based reduction**, for saving computations.

### I. Vertex-Equivalence-based Reduction

Motivation: redundancies induced by common subgraph (cs) isomorphism

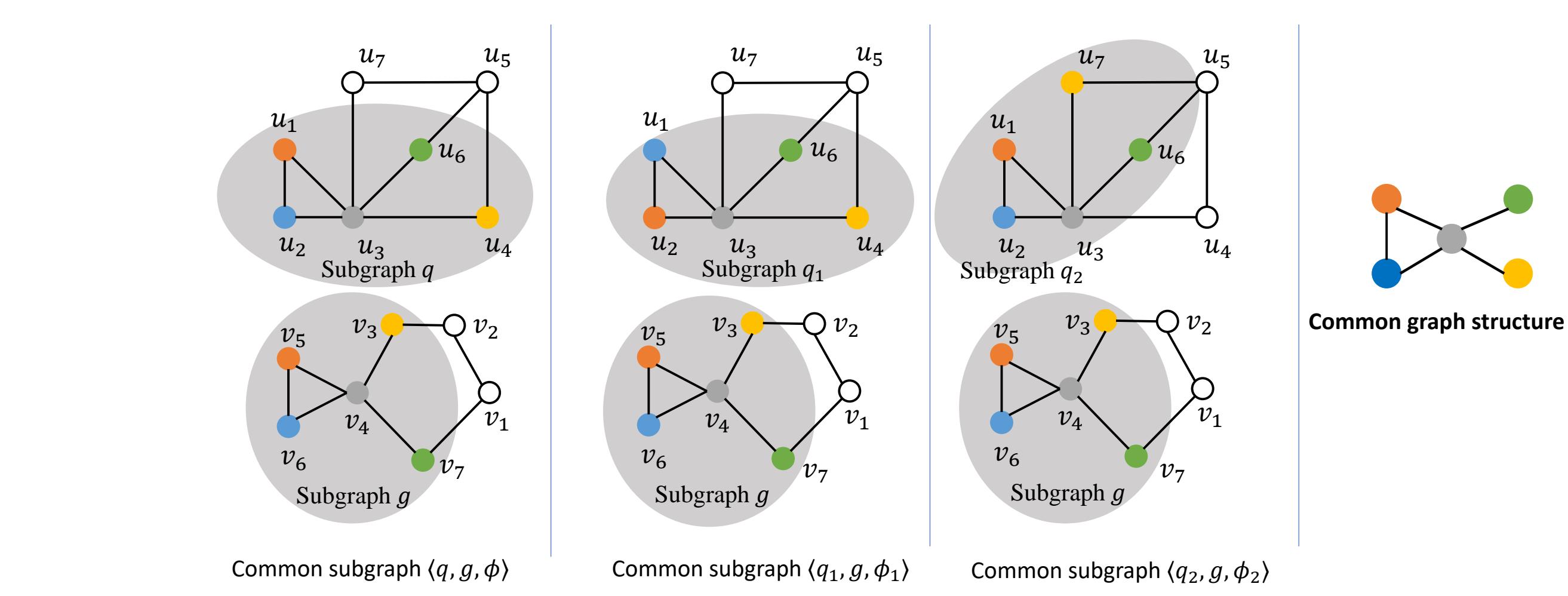


Figure 4.  $\langle q, g, \phi \rangle, \langle q_1, g, \phi_1 \rangle$  and  $\langle q_2, g, \phi_2 \rangle$  are mutually cs-isomorphic since they have the same topological structure. Exploring them via backtracking is redundant.

Idea: reduce the redundancy by vertex-equivalence-based reduction

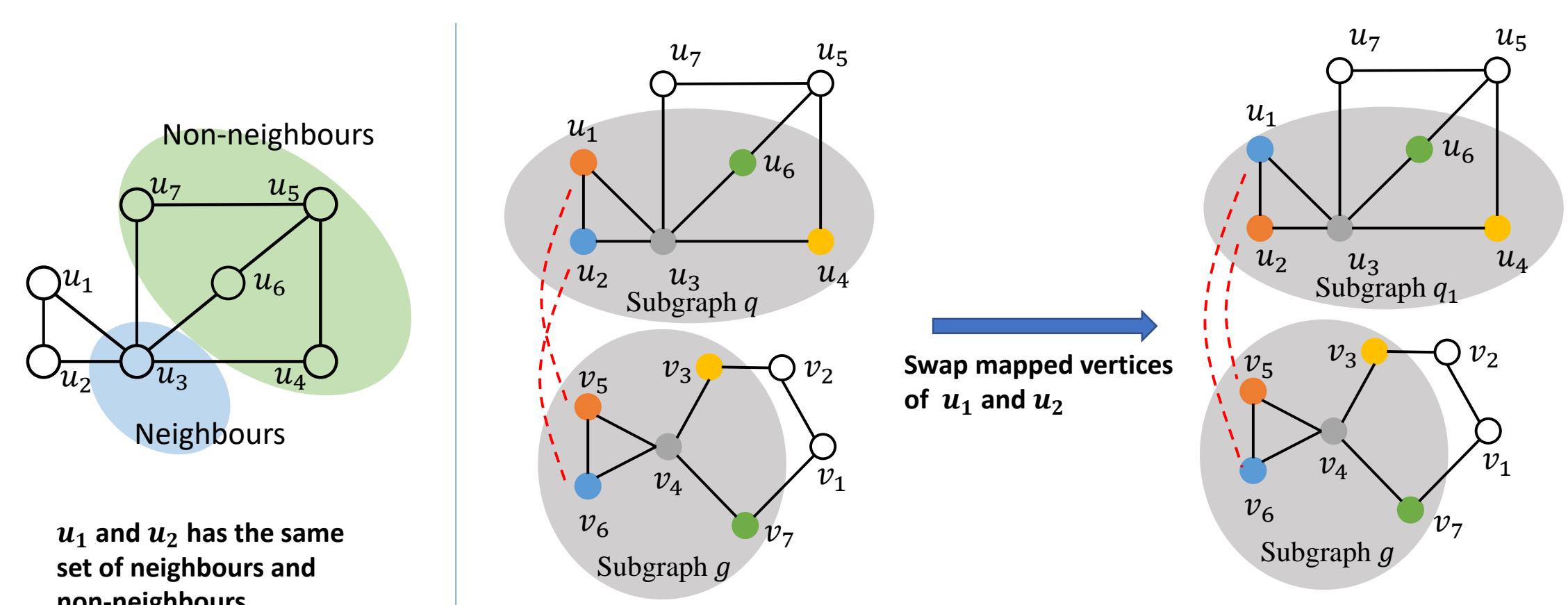


Figure 5. Identify cs-isomorphic common subgraphs based on two structurally equivalent vertices  $u_1$  and  $u_2$

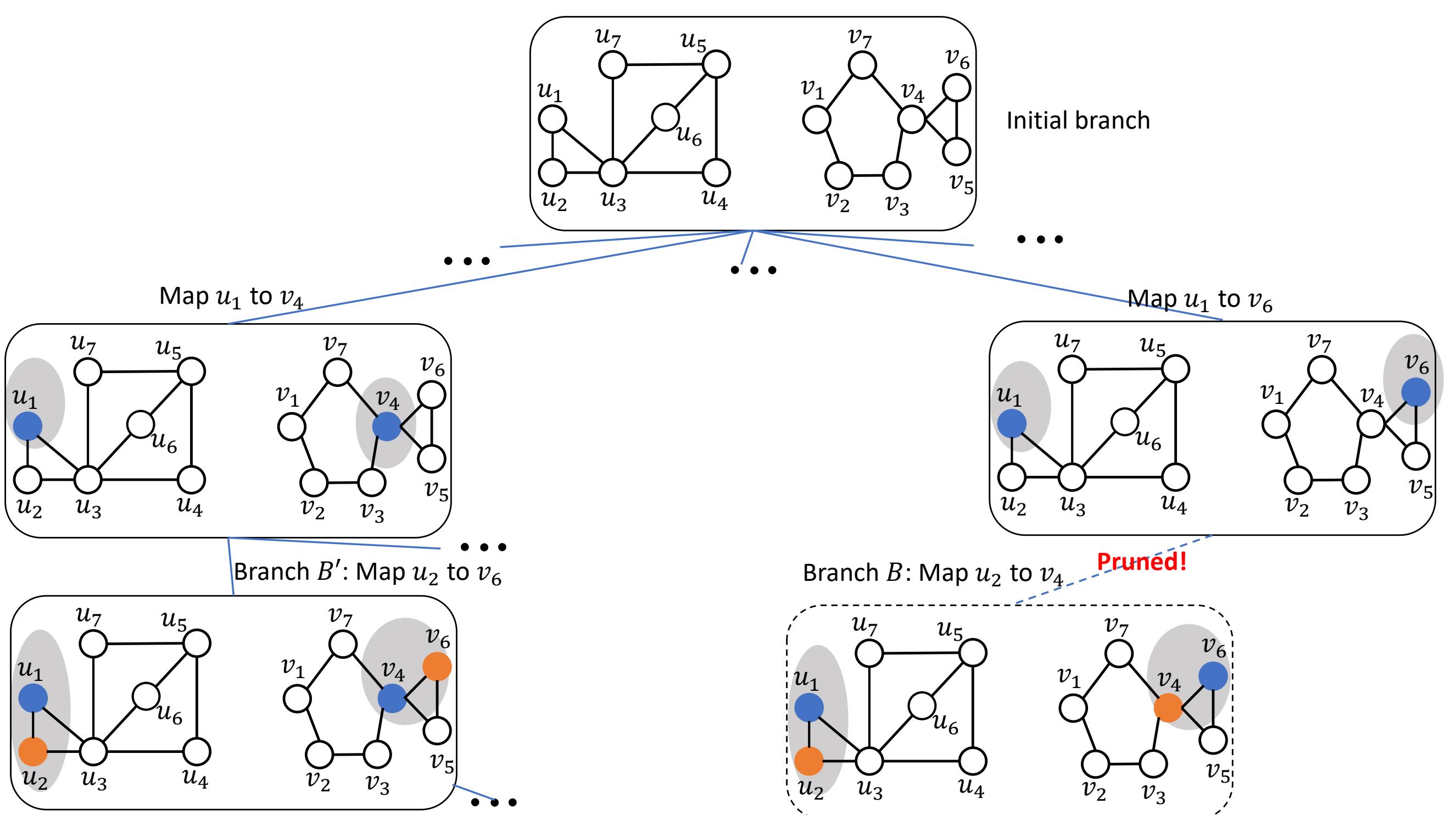


Figure 6. Illustrating the reduction rule. Branch  $B$  can be pruned since we prove that all MCSs found within  $B$  are cs-isomorphic to those found previously in  $B'$  (given  $u_1$  and  $u_2$  are structurally equivalent)

For details of other vertex-equivalence-based reduction rules, please refer to our paper.

### II. Maximality-based Reduction

#### Main idea.

- A maximum common subgraph must be a maximal common subgraph
- Prune those branches that hold non-maximal common subgraphs only

### III. Summary and Analysis

Assume  $|V_G| \geq |V_Q|$ :

- Space complexity:  $O(|V_Q| + |S^*| \times |V_G|)$  ( $S^*$  - the MCS)
- Time complexity:  $O^*((|V_G| + 1)^{|V_Q|})$  ( $O^*$  ignores the polynomials; We remark that the SOTA McSplitDAL [1] runs fast in practice but does not have any theoretical guarantees)

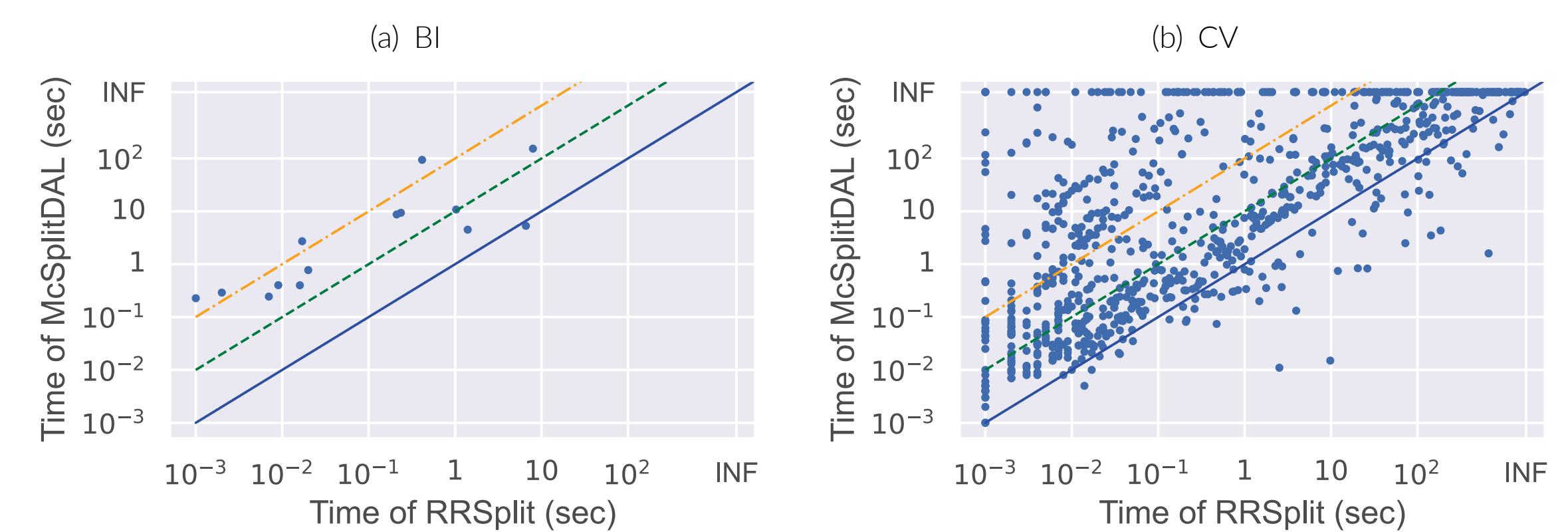
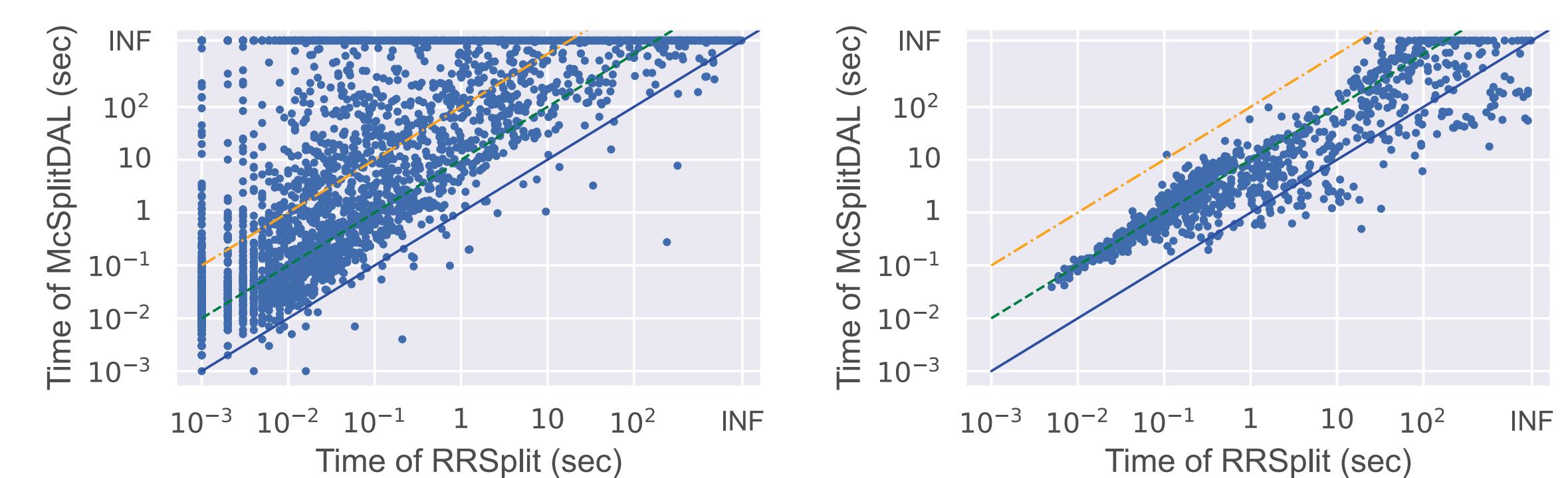
### Experiments

**Dataset:** biochemicalReactions (BI), images-CVIU11 (CV), images-PR15 (PR) and LV (LV)

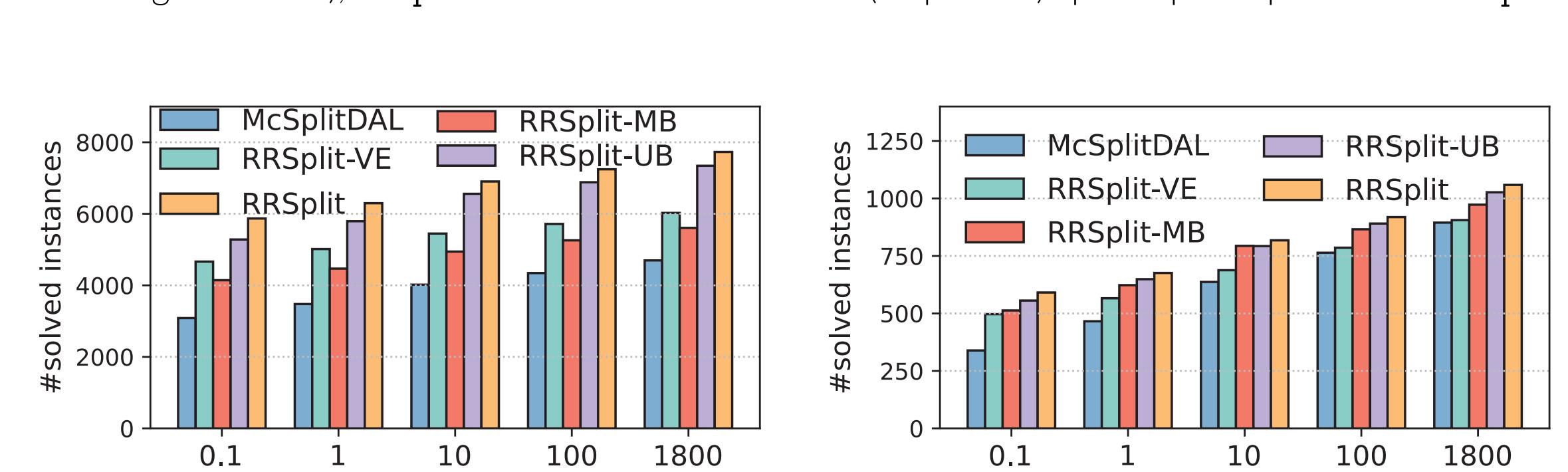
**Baselines:** the state-of-the-art McSplitDAL [1]

Table 1. Datasets used in the experiments ("# of solved instances" refers to the number of instances solved by algorithms within 1,800 seconds and "Achieved speedups" refers to the percentage of the solved instances that RRSPLIT runs at least 5×/10×/100× faster than McSplitDAL)

Dataset	Domain	# of graphs	# of instances	# of vertices	# of solved instances	Achieved speedups
BI	Biochemical	136	9,180	9~386	7,730	4,696 91.3% 84.4% 69.7%
CV	Segmented images	190	6,424	22~5,972	1,351	1,291 76.5% 48.6% 0.2%
PR	Segmented images	25	24	4~4,838	24	24 91.7% 91.7% 58.3%
LV	Synthetic	112	6,216	10~6,671	1,059	883 68.0% 54.7% 38.3%

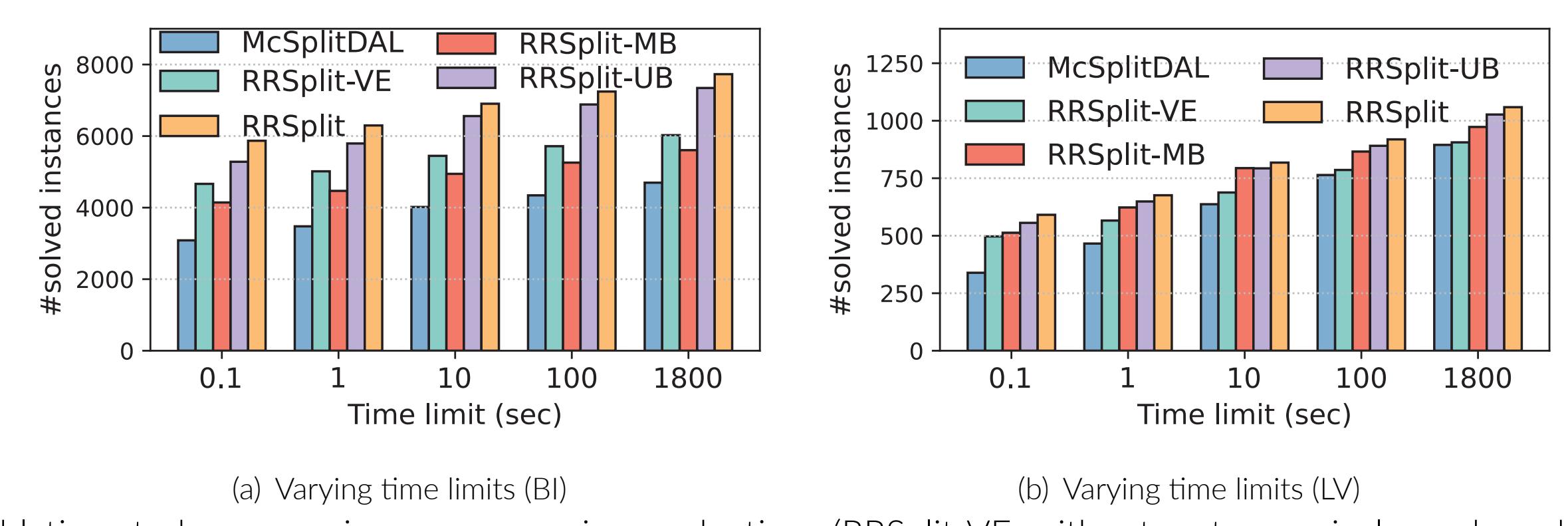


(a) BI (b) CV



(c) PR (d) LV

Figure 7. Running time on all datasets. For those problem instances located at the right side of dash line '-' with orange color (resp. '-' with green color), RRSPLIT achieves at least 100× (resp. 10×) speedup compared with McSplitDAL.



(a) Varying time limits (BI)

(b) Varying time limits (LV)

Figure 8. Ablation study: comparison among various reductions (RRSPLIT-VE: without vertex-equivalence-based reduction, RRSPLIT-MR: without maximality-based reduction, RRSPLIT-UB: without the proposed upper bound)

### References

- [1] Yanli Liu, Jiming Zhao, Chu-Min Li, Hua Jiang, and Kun He. Hybrid learning with new value function for the maximum common induced subgraph problem. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 37, pages 4044–4051, 2023.
- [2] Ciaran McCreesh, Patrick Prosser, and James Trimble. A partitioning algorithm for maximum common subgraph problems. In *Proceedings of the 26th International Joint Conference on Artificial Intelligence*, pages 712–719, 2017.