of edge counts and attribute values; and (2) a comparison of edge counts in subgraphs constrained by attribute value ranges in a Monte Carlo processing. The congruence measure exploits these dependencies between random subgraphs and their attribute subspaces and *ConSub* selects attribute subsets featuring those dependencies in multivariate attribute spaces. This selection can serve as general pre-processing step for algorithms that rely on the homophily assumption on attributed graphs.

As second method, *FocusCO* [1] incorporates the user preference into the selection of relevant subspaces in attributed graphs. *FocusCO* considers communities and community outliers based on user preference. This *focused* mining is of particular interest in attributed graphs, where users might not be concerned with all but a few available attributes. As different attributes induce different clusters and outliers in the graph, the user should be able to steer the subpace selection accordingly. As such, the user controls the mining by providing a set of exemplar nodes (perceived similar by the user) from which *FocusCO* infers *attribute weights* of relevance that capture the user-perceived similarity. The essence of user preference is captured by those attributes with large weights, i.e. the *focus attributes*, which form the basis for the discovery of focused clusters and outliers.

To illustrate the applicability of common graph mining tasks and in order to evaluate these selection schemes, community detection and community outlier mining is used. The methods are evaluated on several synthetic and real world graphs, in particual on a novel benchmark graph for attributed graphs that has been derived from a case study on the Amazon co-purchase network [5]. The selection of congruent subspaces clearly enhances outlier detection by measuring outlierness scores in selected subspaces only. Furthermore, focused attributes enable a more user-oriented mining of community structures. Experiments show that both approaches outperform traditional full space approaches and as general pre-processing steps they enhance the later data mining steps on attributed graphs.

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