

Table 4 A brief comparison of community detection methods in multilayer networks

Name	Classification	Strategy	Complexity ^a	Network
PMM (Tang et al. 2009)	Aggregation	Multilayer modularity maximization	$O(n^3 L)$	Multi-dimensional
MULTICLUS (Papalexakis et al. 2013)	Aggregation	Minimum description length	$O(mnIC^2)$	Multiplex, bipartite
GRAPHFUSE (Papalexakis et al. 2013)	Aggregation	Tensor analysis	$O(n^3 L)$	Multiplex
ABACUS (Berlingerio et al. 2013) ^b	Aggregation	Multilayer modularity maximization	–	Multi-dimensional
DNMF (Jiao et al. 2017)	Aggregation	Nonnegative matrix factorization	$O(n^2 L)$	Multiplex, temporal
EMCD (Tagarelli et al. 2017) ^c	Aggregation	Modularity maximization	$O(I(m + LC))$	Multiplex
Multilink (Mondragon et al. 2018)	Aggregation	Multilink similarity	$O(m^2)$	Multiplex
M-EMCD* (Mandaglio et al. 2018)	Aggregation	Modularity maximization	$O(I(m + LC))$	Multiplex
M-Motif (Huang et al. 2019)	Aggregation	Merge partitions across layers	$O(n \log(n) L^2)$	Multilayer
MEMM (Zhang et al. 2019)	Aggregation	Multilayer edge mixture model	$O(n^2)$	Multiplex
HSBM (Paez et al. 2019)	Aggregation	Hierarchical SBM and Bayes	$O(n^2 LC^2)$	Multiplex
Variational-Bayes (Ali et al. 2019)	Aggregation	SBM and variational Bayes	$O(n^2 L^2 C)$	Multiplex, weighted
GenLouvain (Jutla et al. 2011)	Direct	Multiplex map equation	$O(n^2 \log n)$	Multiplex, temporal
MultiGA (Amelio and Pizzuti 2014b)	Direct	Genetic representation	$O(In^2 L)$	Multiplex
MultiMOGA (Amelio and Pizzuti 2014a)	Direct	Multi-objective optimization	$O(LCn^2)$	Multiplex
CLAN (Dabideen et al. 2014)	Direct	Variational label propagation	$O(LInK)$	Multiplex, temporal
LART (Kuncheva and Montana 2015)	Direct	Random walk	$O(m^3)$	Multiplex
Multiplex-Infomap (De Domenico et al. 2015a)	Direct	Multiplex map equation	$O(n^2)$	Multiplex
LocalNCPs (Jeub et al. 2015) ^d	Direct	Local random walk	$\geq O(nIKL)$	Multiplex
BAZZI (Bazzi et al. 2016)	Direct	Multilayer modularity maximization	$O(nI^2 L)$	Multiplex, temporal
ML-LCD (Interdonato et al. 2017)	Direct	Local objective function maximization	$\geq O(C^3 K^2 L)$	Multiplex

Table 4 continued

Name	Classification	Strategy	Complexity ^a	Network
GN- Q_M (Pramanik et al. 2017)	Direct	Maximum betweenness edges removal	$O(nm^2)$	Multiplex
Louvain- Q_M (Pramanik et al. 2017)	Direct	Modularity optimization	$O(m^3)$	Multiplex, weighted
MLMaOP (Pizzuti and Socievole 2017) ^e	Direct	Multi-objective Optimization	–	Multiplex
NFC (Aslak et al. 2018)	Direct	Random walk and Infomap	$O(m(n + m))$	Multiplex, temporal
S2-jNMF (Ma et al. 2018)	Direct	Nonnegative matrix factorization	$O(rn^2 km)$	Multiplex
MNLPA (Alimadadi et al. 2019)	Direct	Label Propagation	$O(nk)$	Multiplex, directed, weighted
IterModMax (Pamfil et al. 2019)	Direct	SBM and Modularity maximization	$O(n^2 L)$	Multiplex, temporal
TMSCD (Kuncheva and Montana 2017, 2019)	Direct	Spectral graph wavelet	$O(n^2 L)$	Multiplex, temporal
CMNC (Chen et al. 2019)	Direct	Tensor Decomposition	$O(n^3 L)$	Multiplex
MCD-Berlingerio (Berlingerio et al. 2011a) ^f	Flattening	Employing monolayer algorithms	–	Multi-dimensional
CDHIA (Tang et al. 2012b)	Flattening	network integration and k -means	$\geq O(nICK)$	Multi-dimensional
AggregationPan (Pan et al. 2018)	Flattening	Cutting edges with weight < threshold	$O((m + n)L)$	Multiplex, weighted
ParticleGao (Gao et al. 2019)	Flattening	Particle Competition	$O(nICL^2)$	Multiplex, directed, weighted

^a n and m are the number of nodes and edges, respectively. L is the number of layers, K is the average degree of nodes, I denotes the iteration times.^b The complexity of ABACUS depends on the complexity of the employed monolayer algorithms, e.g., $O(n)$ from LPA (Raghavan et al. 2007) and with total complexity of $O(LCN^2)$.^c I denotes the number of iterations to convergence at a local optimum; C is the number of communities.^d LocalNCPs is a local community detection algorithm. For a given node, the complexity is approximately $O(LInK/C)$. For C partitions, the minimum complexity is $O(LInK)$.^e The complexity of MLMaOP depends on an uncertain convergence process, thereby marked with “–”.^f This algorithm provides a framework via flattening a multi-dimensional network into a weighted network, and then employs the existing monolayer algorithms for community detection, thereby the complexity is uncertain