network learning

introduction to network analysis (ina)

Lovro Šubelj University of Ljubljana spring 2024/25

learning tasks

modern machine learning with network data

- node-level tasks
 - node classification (e.g. finding hoaxes on Wikipedia)
 - node ranking (e.g. finding top influencers on Instagram)
 - network clustering (e.g. research areas of scientific papers)
- edge-level tasks
 - link prediction (e.g. product recommendation on Amazon)
 - strength of ties (e.g. close friends/acquaintances on Facebook)
- graph-level tasks
 - graph classification (e.g. playing strategy in football)
 - graph generation (e.g. good candidates for new drugs)
 - etc.

learning since ~2000

use network analysis techniques directly

node ranking tasks

node centrality, link analysis, graphlets, egonets etc.

— link prediction tasks

link bridging, prediction indices, matrix factorization etc.

network clustering tasks

community detection, (stochastic) blockmodeling etc.





learning until ~2010

use network analysis techniques for features

- 1. generate *node/link/graph* features from *network* structure
- 2. feed generated *features* into *machine learning* method



but *features* are *task dependent* & redesigned every time!

for *survey* see [ZPS⁺16]

learning modern

use machine learning methods for embeddings/directly

- 1. dimensionality reduction/matrix factorization (e.g. NMF) decomposition of adjacency matrix A or graph Laplacian L
- random walks on network (e.g. node2vec [GL16], struct2vec [FRS17]) similar nodes have similar embeddings independently of task
- graph neural networks (e.g. GCN [KW17], GAT, GraphSAGE [HYL17]) node/edge/graph representations are learned for specific task

for *survey* see [MKNŠ21]

learning node2vec



learning GraphSAGE

$$h_i^0 = x_i$$
$$h_i^k = \sigma \left(W_k \cdot \text{CONCAT}(h_i^{k-1}, \text{AGGREGATE}_k(\{h_j^{k-1} \mid j \in \Gamma_i\})) \right)$$



for *paper* see [HYL17]

learning references



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