network *learning*

introduction to network analysis (ina)

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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.







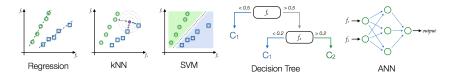


— etc.

learning until \sim 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]

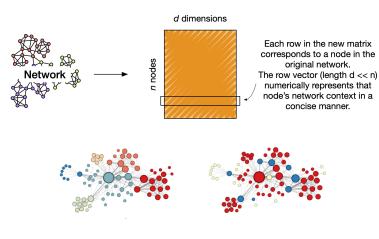
learning modern

use machine learning methods for embeddings/directly

- dimensionality reduction/matrix factorization (e.g. NMF) decomposition of adjacency matrix A or graph Laplacian L
- 2. random walks on network (e.g. node2vec [GL16], struct2vec [FRS17]) similar nodes have similar embeddings independently of task
- 3. 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

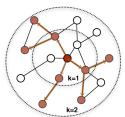


for *paper* see [GL16]

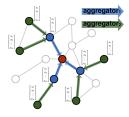
learning GraphSAGE

$$h_i^0 = x_i$$

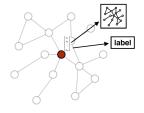
$$h_i^k = \sigma\left(\frac{W_k \cdot \text{CONCAT}(h_i^{k-1}, \text{AGGREGATE}_k(\{h_j^{k-1} \mid j \in \Gamma_i\}))}{} \right)$$



1. Sample neighborhood



2. Aggregate feature information from neighbors



Predict graph context and label using aggregated information

for *paper* see [HYL17]

learning references



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