

# network *learning*

introduction to *network science in Python* (*NetPy*)

Lovro Šubelj  
University of Ljubljana  
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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)

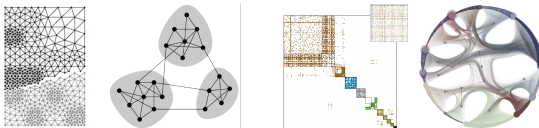
## — *graph-level tasks*

- graph classification (e.g. playing strategy in football)
- graph generation (e.g. good candidates for new drugs)
- etc.

# learning *since* $\sim 2000$

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.

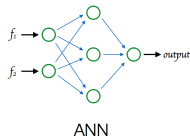
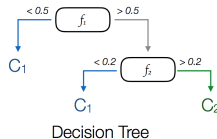
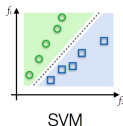
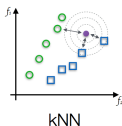
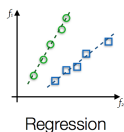


— etc.

# 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<sup>+</sup>16]

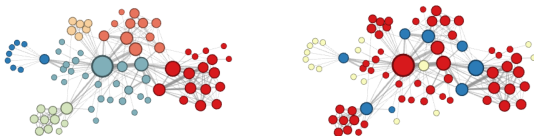
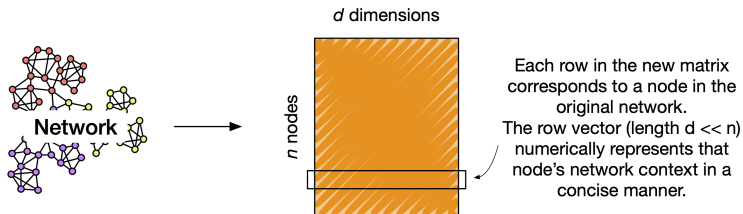
# learning *modern*

use *machine learning* methods for *embeddings/directly*

1. dimensionality reduction/*matrix factorization* (e.g. NMF)  
*decomposition* of adjacency matrix  $A$  or graph Laplacian  $L$
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*

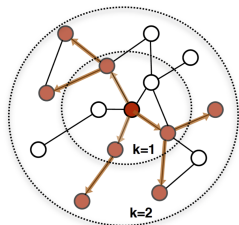


for *paper* see [GL16]

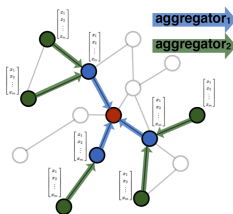
# learning *GraphSAGE*

$$h_i^0 = x_i$$

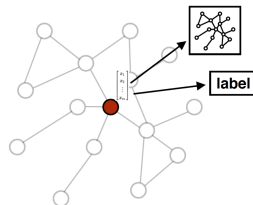
$$h_i^k = \sigma \left( W_k \cdot \text{CONCAT}(h_i^{k-1}, \text{AGGREGATE}_k(\{h_j^{k-1} \mid j \in \Gamma_i\})) \right)$$



1. Sample neighborhood



2. Aggregate feature information from neighbors



3. Predict graph context and label using aggregated information

for *paper* see [HYL17]

# learning *references*



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