network *learning*

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

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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

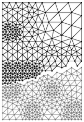
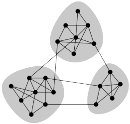
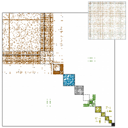
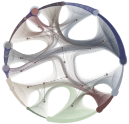
  node centrality, link analysis, graphlets, egonets etc.

- *link prediction* tasks

  link bridging, prediction indices, matrix factorization etc.

- *network clustering* tasks

  community detection, (stochastic) blockmodeling etc.

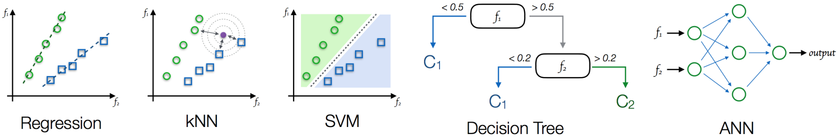





- etc.

learning *until 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*

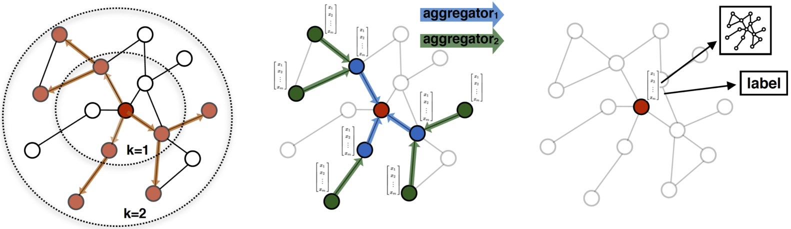
1. dimensionality reduction/*matrix factorization* (e.g. NMF)
   decomposition of adjacency matrix A or graph Laplacian L
2. *random walks* on network (e.g. node2vec [GL16], struct2vec [FRS17])
   similar nodes have *similar embeddings* independently of task
3. *graph neural networks* (e.g. GCN [KW17],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

for *survey* see [MKNŠ21]

learning *GraphSAGE*

$$h_i^0 = x_i$$

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



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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