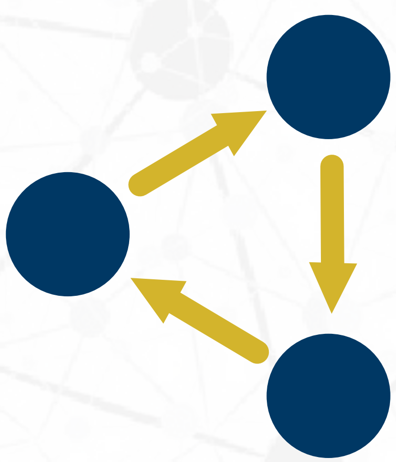
東京工業大学
Tokyo Institute of Technology

MURATA LAB



Mid-term Presentation

Motif-aware method for graph analysis

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2017/02/03

Roadmap

Result of motif methods | Proposal of future models

Deep architecture
Skip-gram methods
Spectral methods
EMBEDDINGS

Diversity models
Generative models
Motif Spectral
IN PROGRESS

NETWORK MOTIF
Definition
Applications
Motif Conductance

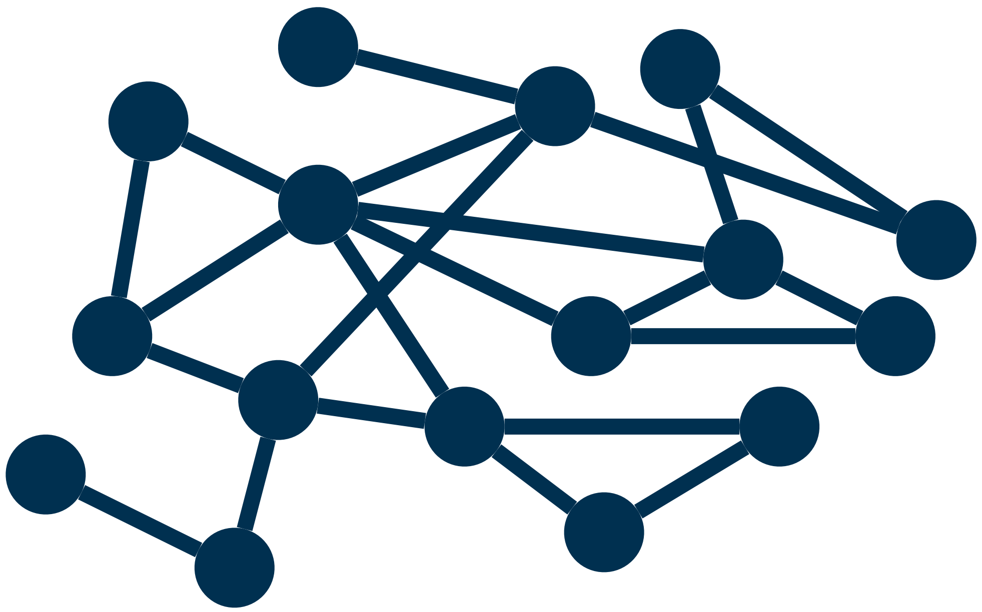
OBSERVATION
Experiments
Proposed models
Results

Definition and applications

Complex networks and significant subgraphs

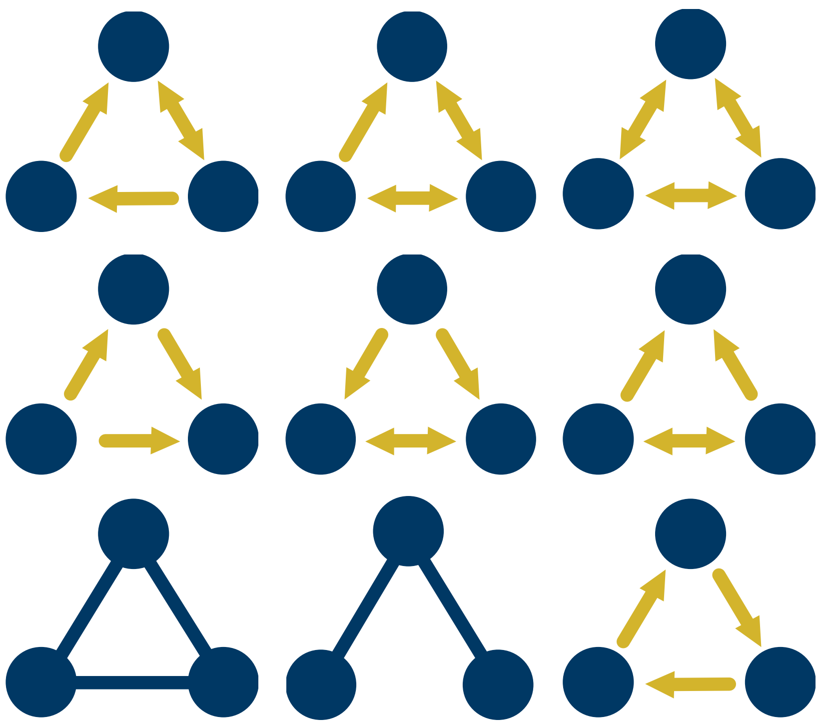
Scales of network analysis:

- Macroscopic (global view)
- Microscopic (interactions)
- Mesoscopic (sub-structures)



Network motifs are [1]

> patterns of statistically significant interconnections occurring in complex networks.



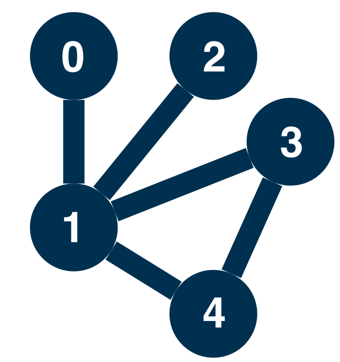
Applications

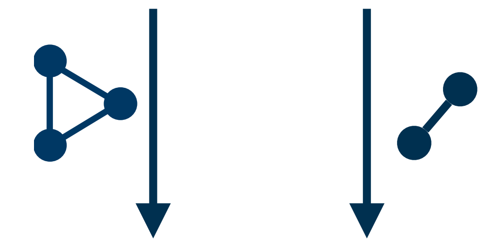
- Social networks [2]
- Biological systems [1,3,4]

[4] (Franceschet, 2012) [3] (Honey, 2007) [2] (Holland, 1970) [1] (Milo, 2002)

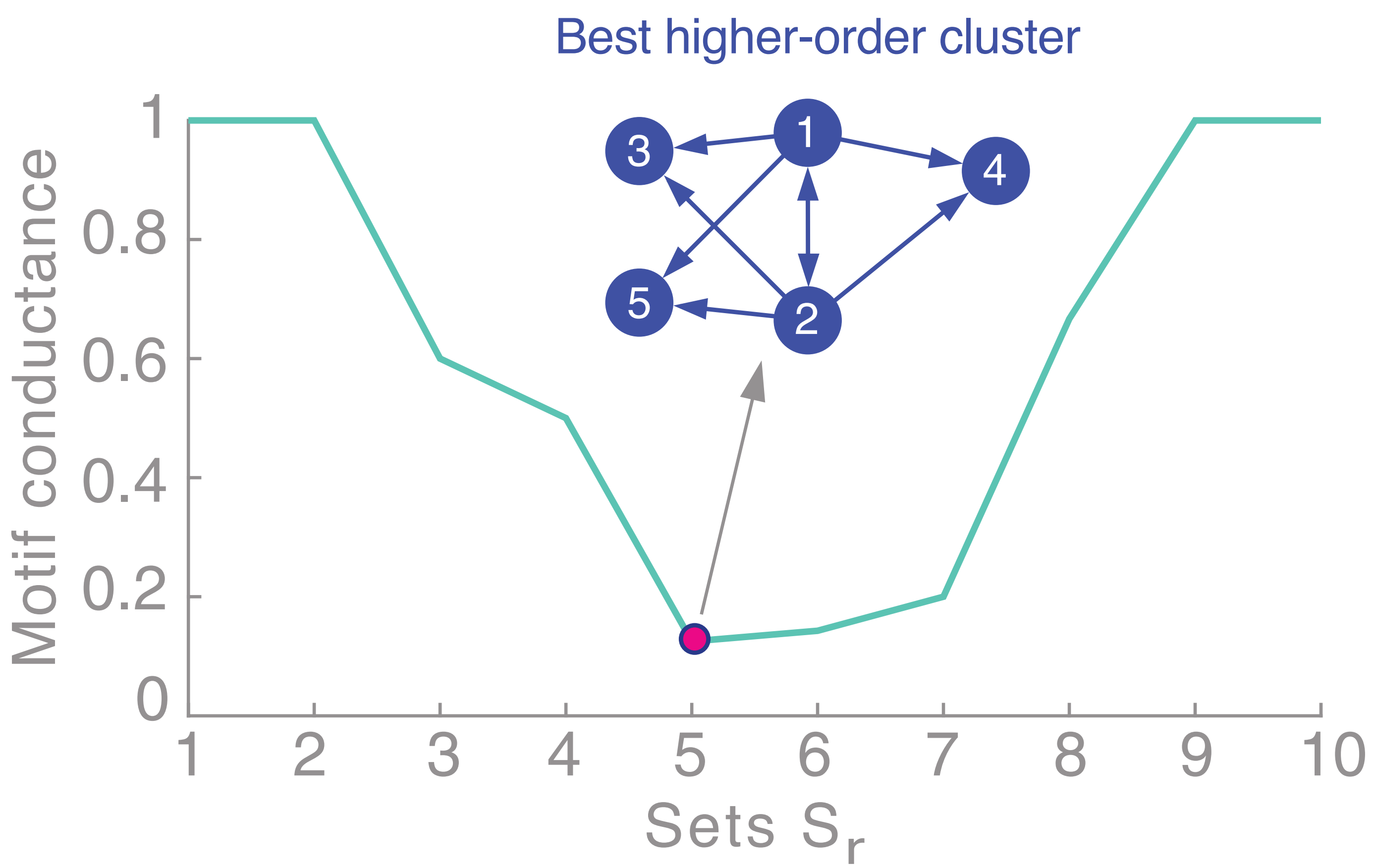
Motif conductance *(Benson, 2016)*

- Generalization of graph conductance.
- Motif-cooccurrence matrix.
- Good results for graph partitioning.





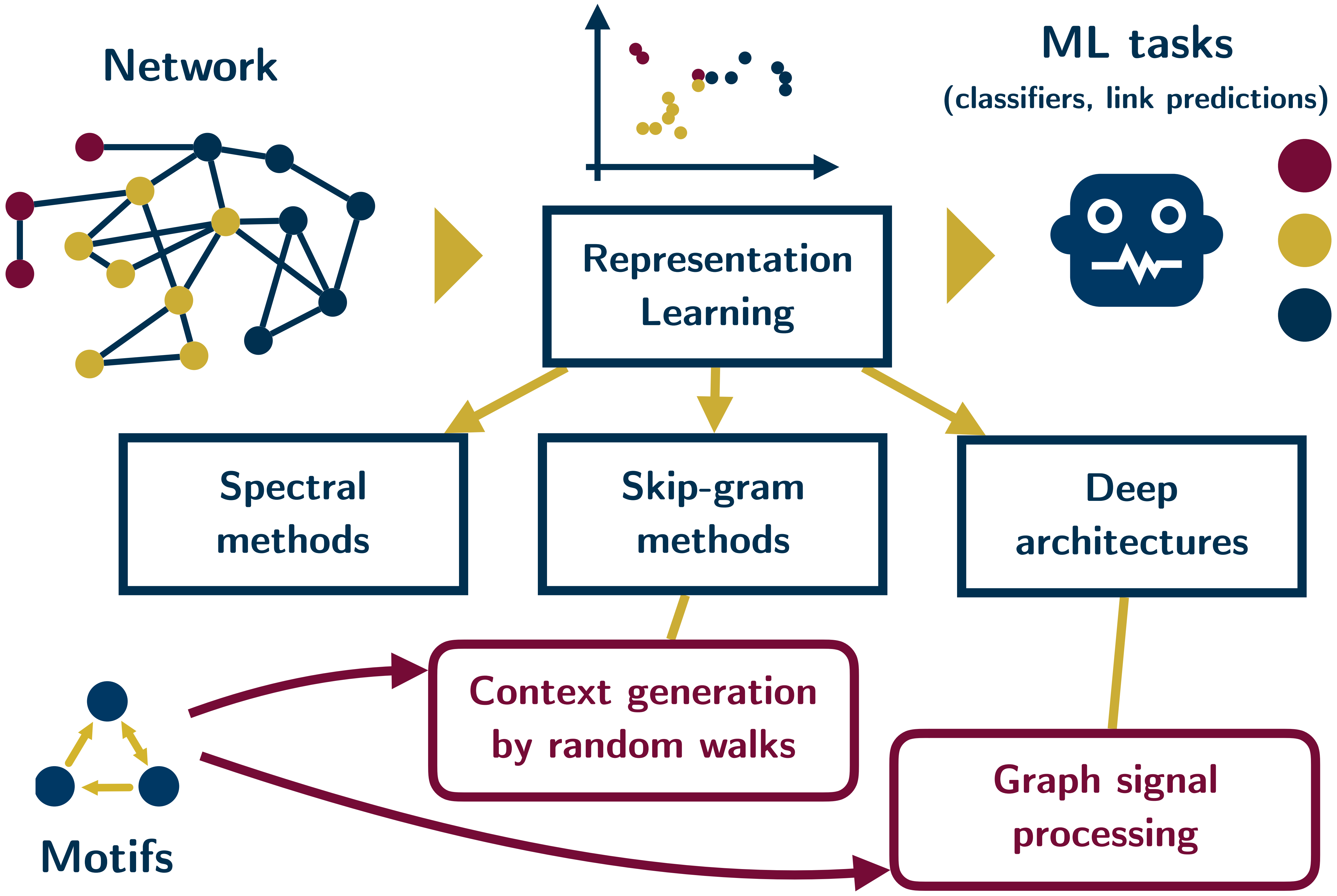
$$\begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 2 & 2 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 2 \\ 0 & 2 & 0 & 2 & 0 \end{bmatrix}$$



$$\phi_m(S) = \frac{\mathrm{cut}_M(S, \bar{S})}{\min[\mathrm{vol}_M(S), \mathrm{vol}_M(\bar{S})]}$$

Representation Learning

Motif-aware approaches



Datasets:

- Blogcatalog3
- Cora, Citeseer, Pubmed
- Facebook (EgoNet)
- Transcription networks

Networks	***#nodes***	***#edge***
Blogcatalog3	10312	333983
Cora*	2708	5429
Citeseer*	3327	4732

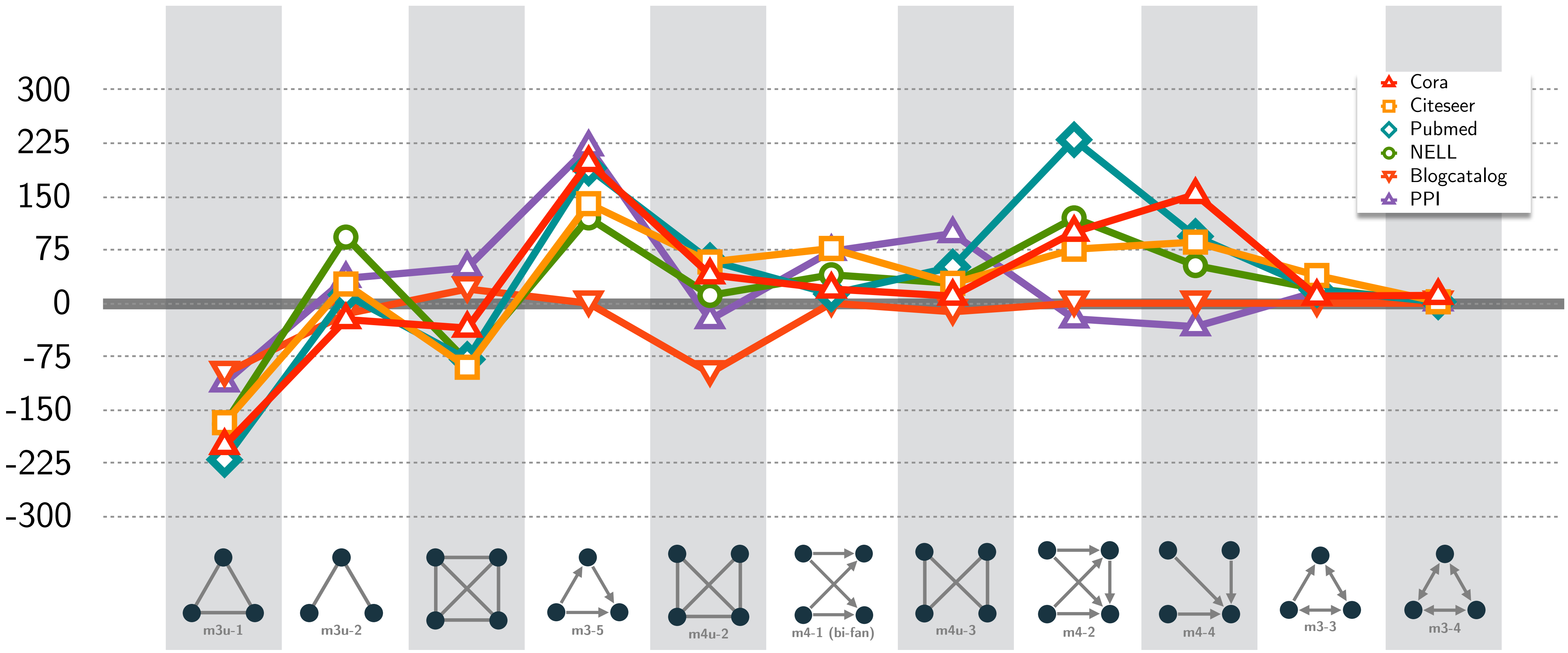
* Each node has a feature vector (tf-idf)

Deciding motif:

- Motif frequency
- Z-score
- Motif conductance

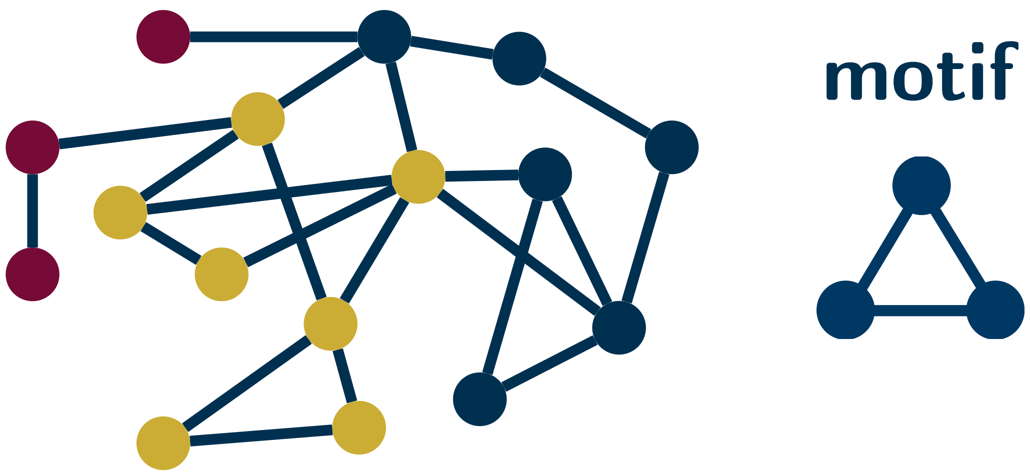
$$z_m = \frac{N_m(emp) - N_m(rnd)}{\sigma_m}$$

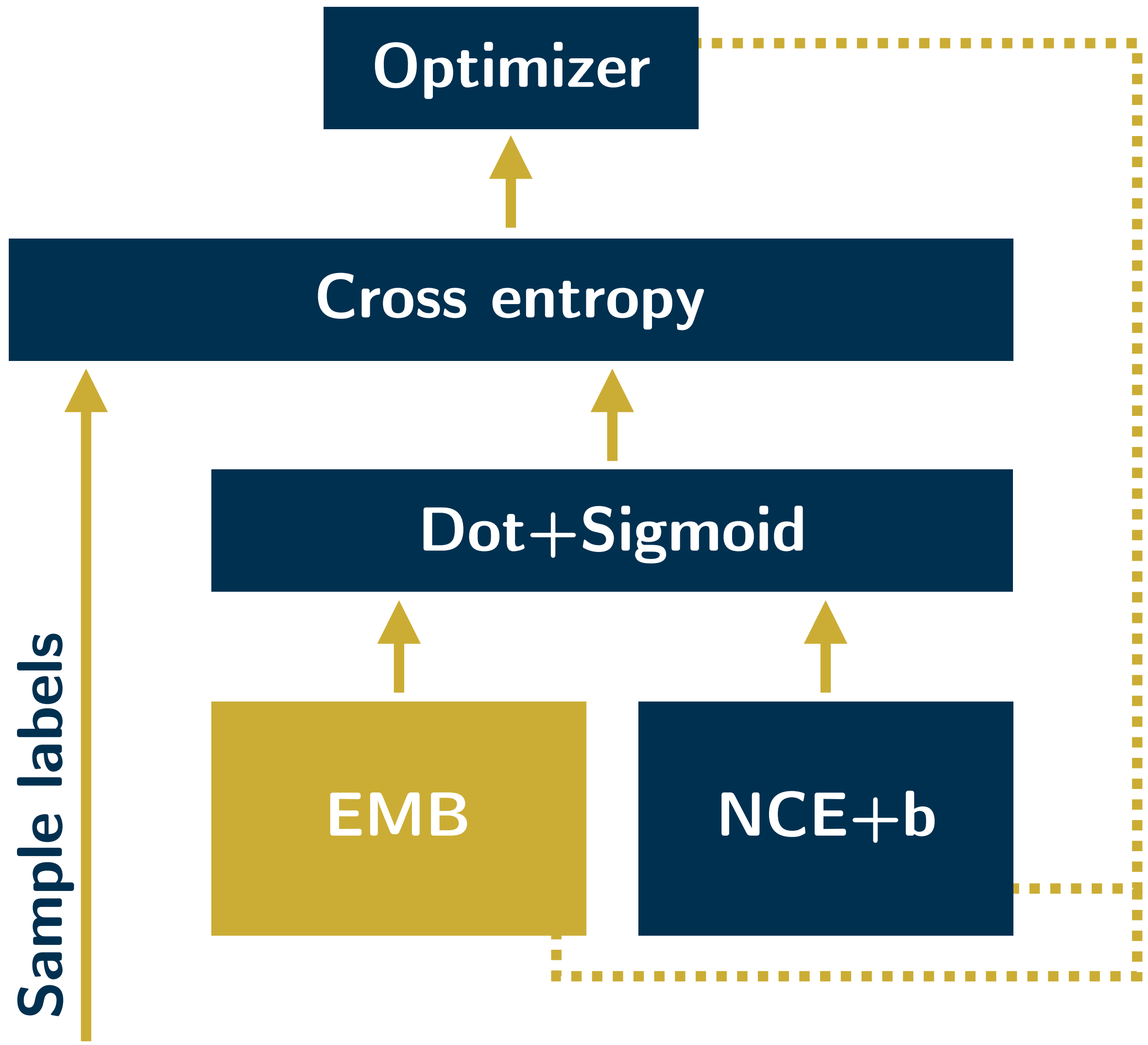
Significant graph - Directed size 3 motifs



Using motif as a guiding pattern

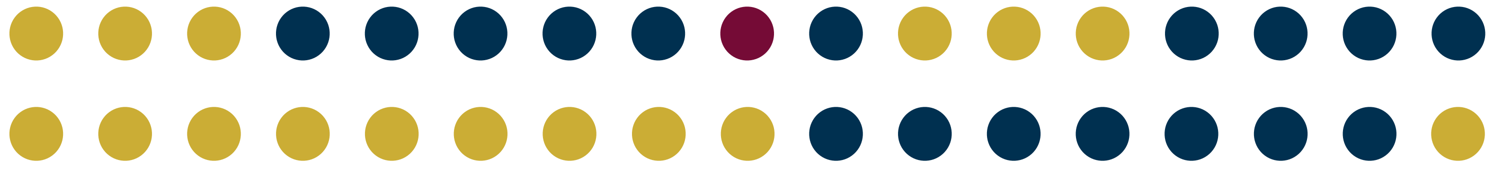
- DeepWalk := Skip-gram+RW
- LINE := DeepWalk+bi-fan
- node2vec := Skip-gram
  +bias-ed walk
- motifwalk := Skip-gram
  +motif walk





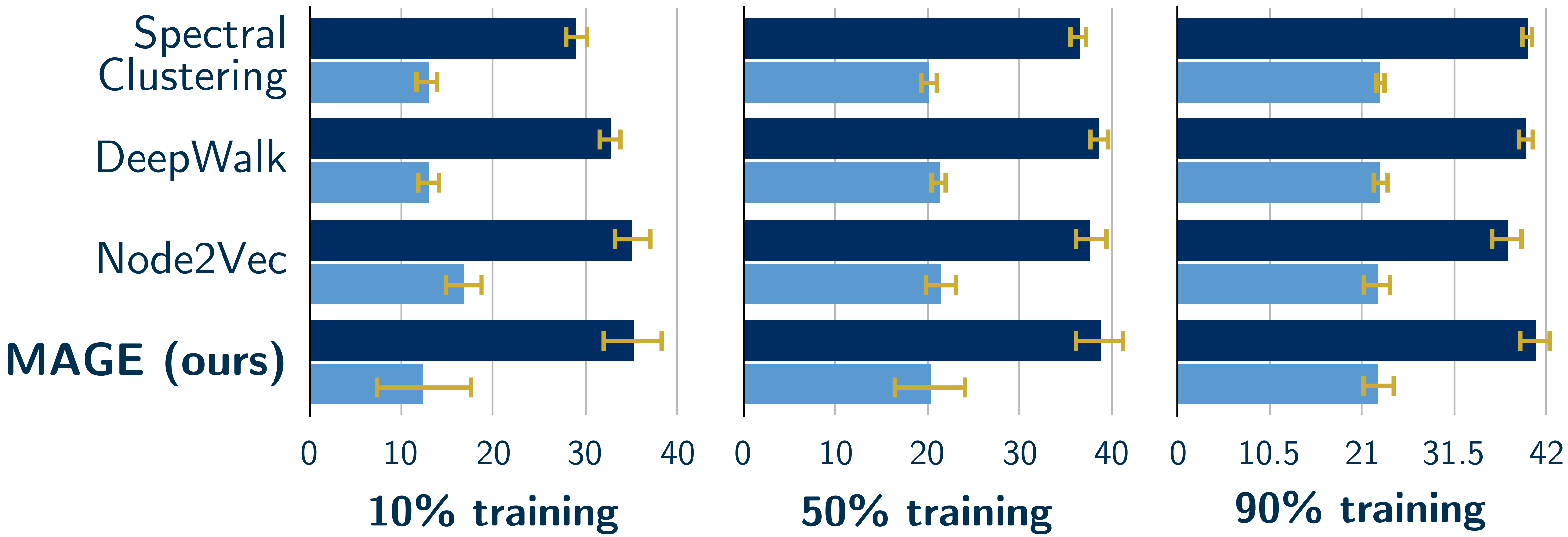
Generated context:

Motif context:



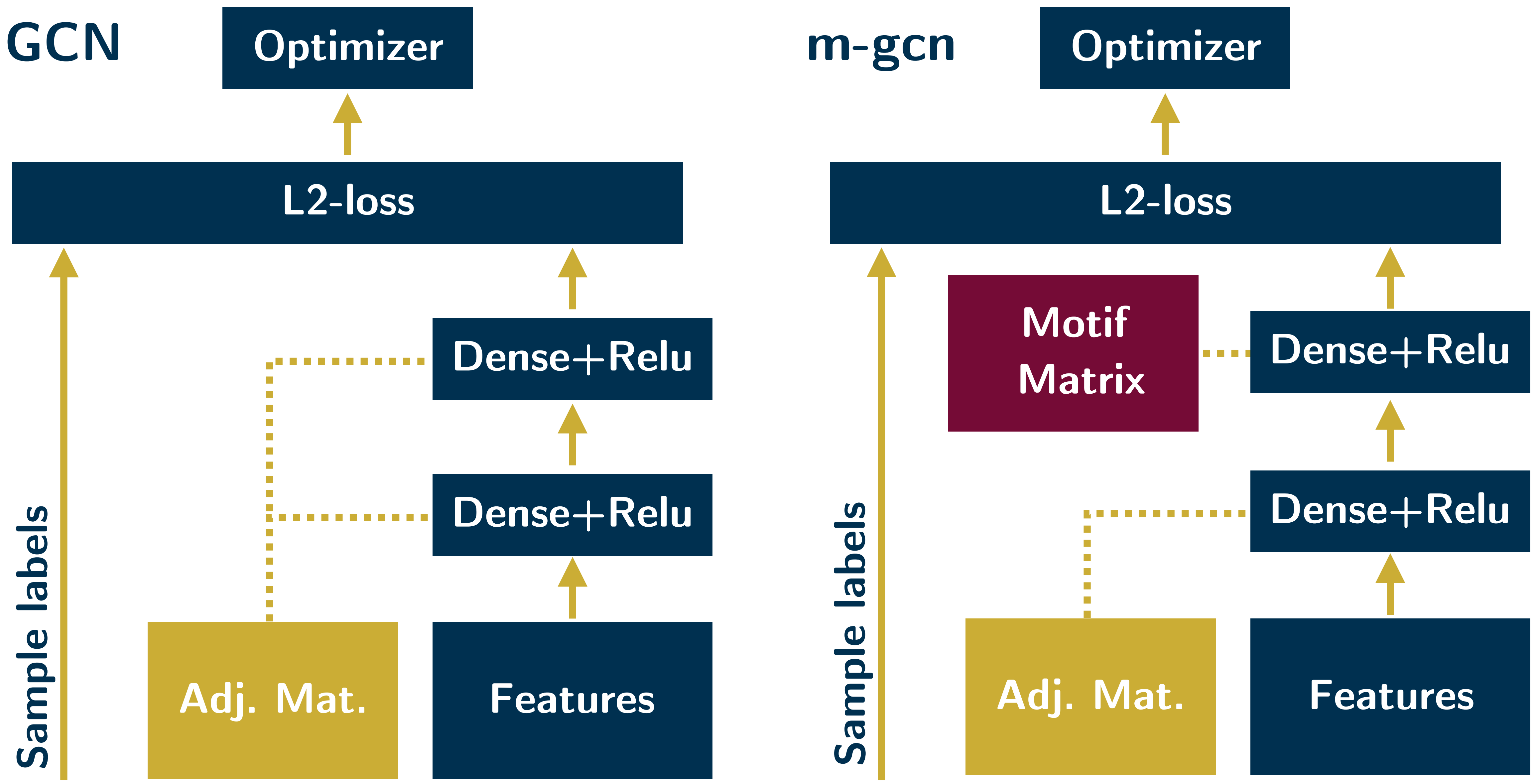
Node multi-label classification

- Blogcatalog3 - f1 score
- 39 classes (imbalanced), nodes can have multiple labels



- Bottleneck at context generation.

Motif laplacian for graph convolutional networks



(Kipf, 2016) (Kipf, 2017)

Node label classification

- Citation networks: Cora, citeseer, pubmed. - f1 and acc.
- 3 to 6 classes, each node has exactly one label.

Methods	Cora	Citeseer	Pubmed
Spectral Clus.	59.5	42.7	65.3
DeepWalk	67.2	43.2	65.3
GCN	81.5	70.3	79.0
m-gcn (ours)	**83.3**	**71.4**	**80.4**

- Explaining why does it work.
- Motif search and co-occurence matrix construction.

My interests:

- Network sampling (diversity oriented).
- Turn m-gcn into a generative model.

Agenda:

- Investigate graph spectral theory.
- Determinantal processes on graphs.
- Graph motif sampling model definition.
- (opt.) Generative Adversarial Networks and Auto-Encoders.

References

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(Alon, 2007) Network motifs: theory and experimental approaches.

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(Kipf, 2016) Variational Graph Auto-encoder.

(Kipf, 2017) Semi-Supervised Classification with Graph Convolutional Networks

$x_2 + y_1 = 100$

$$x_2 + y_1 = 100$$