Classification Supported by Community-Aware Node Features

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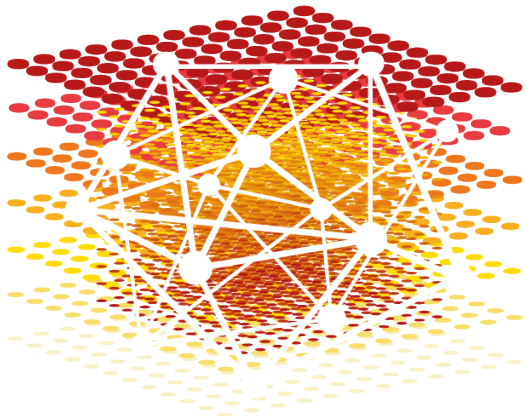
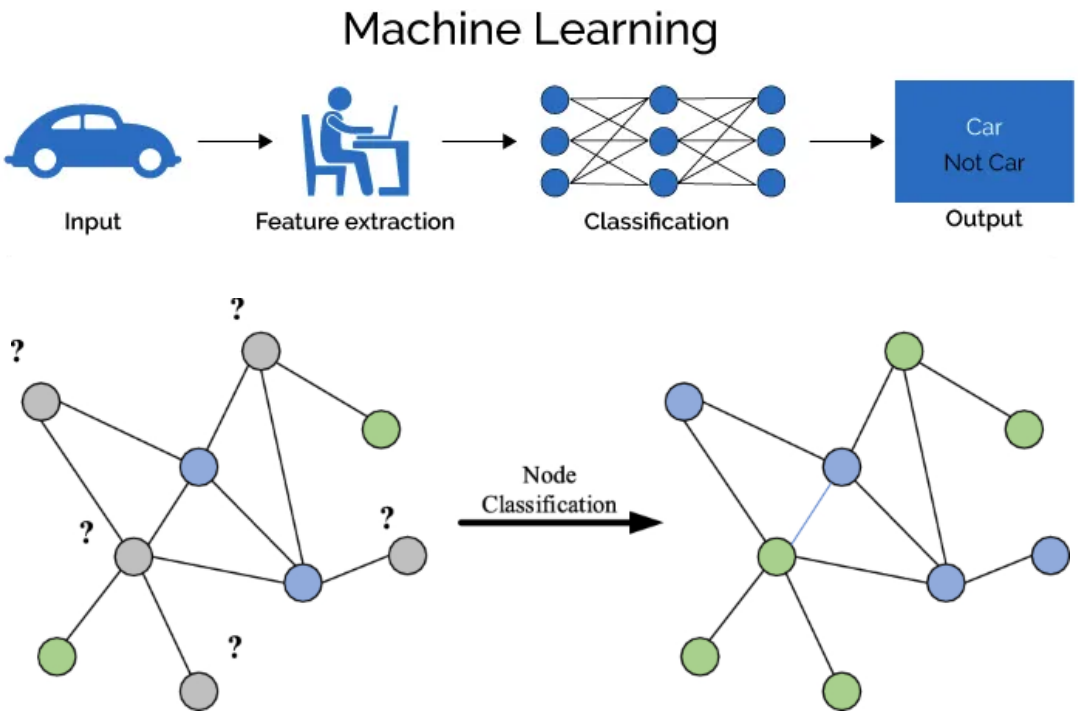


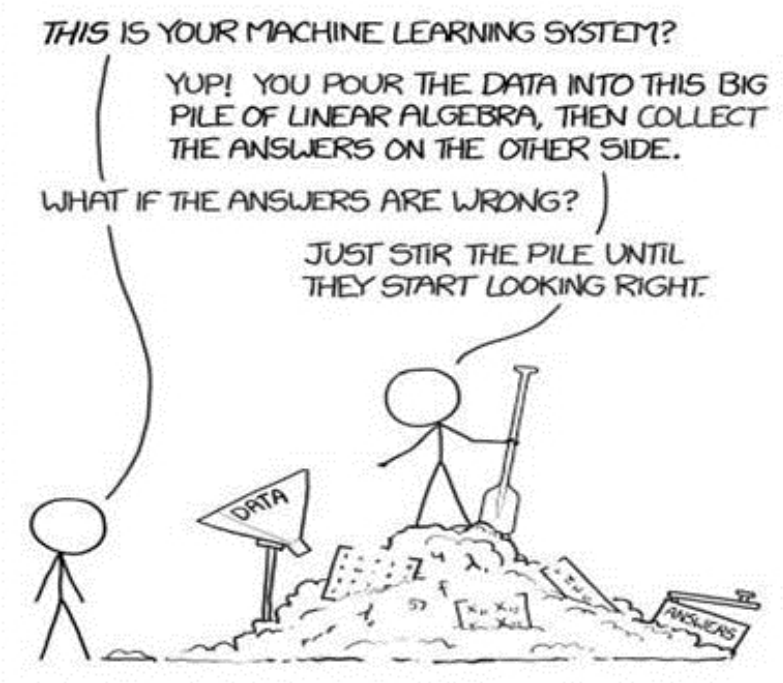
Motivation



Node classification is an important problem in which data is represented as a network, and the goal is to predict labels associated with its nodes.

Practical applications: recommender systems, social network analysis, or applied chemistry.

Node Features



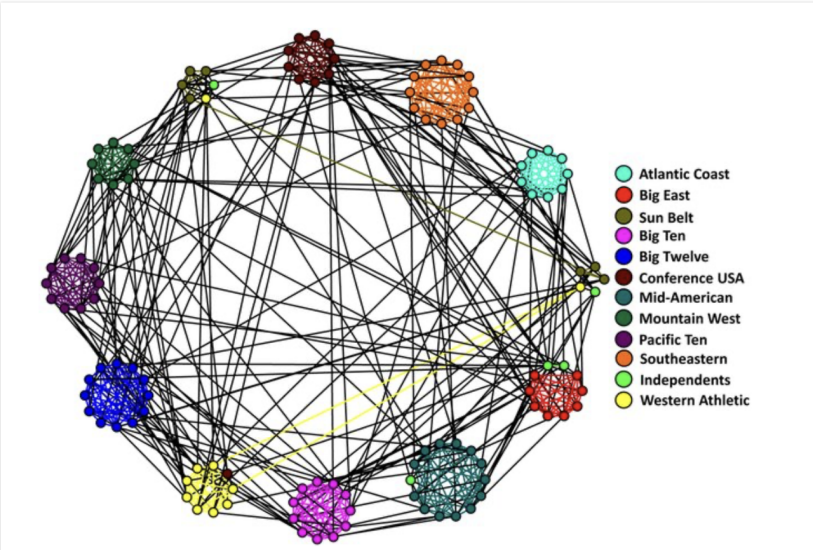
No matter how sophisticated classifiers one builds, they will perform poorly if they do not get informative input concerning the problem. We must have access to a set of highly informative node features that can discriminate representatives of different classes.

Classical Node features - Graph measures

abbreviation	name
`lcc`	local clustering coefficient
`bc`	betweenness centrality
`cc`	closeness centrality
`dc`	degree centrality
`ndc`	average degree centrality of neighbours
`ec`	eigenvector centrality
`eccen`	node eccentricity
`core`	node coreness
`n2v`	16-dimensional `node2vec` embedding
`s2v`	16-dimensional `struc2vec` embedding

We investigate a family of features that pay attention to **community structure** in complex networks.

Community-aware features



The community structure of real-world networks often reveals the internal organization of nodes.

Identifying communities in a network can be done unsupervised and is often the analysts' first step.

Features already introduced in the literature:

A partition $\mathrm{A} = \{A_1, A_2, \ldots, A_\ell\}$ of V into ℓ communities.
Each part A_i ($i \in [\ell]$) is denser comparing to the global density of the graph. $\deg_{A_i}(v)$: the number of neighbours of v in A_i

Participation coefficient of a node v

$$p(v) = 1 - \sum_{i=1}^{\ell} \left(\frac{\deg_{A_i}(v)}{\deg(v)} \right)^2$$

Anomaly score CADA

$$\mathrm{cd}(v) = \frac{\deg(v)}{d_{\mathrm{A}}(v)}$$

where $d_{\mathrm{A}}(v)$ maximum number of neighbouring nodes that belong to the same community.

T.J. Helling et all, A community-aware approach for identifying node anomalies in complex networks.2019

Community-aware features

Normalized within-module degree of a node v

$$z(v) = \frac{\deg_{A_i}(v) - \mu(v)}{\sigma(v)}$$

where $\mu(v)$ and $\sigma(v)$ are, respectively, the mean and the standard deviation of $\deg_{A_i}(u)$ over all nodes u in the part v belongs to.

Normalized anomaly score for a node v

$$\overline{\mathrm{cd}}(v) = \frac{\deg_{A_i}(v)}{\deg(v)}$$

Other Measures

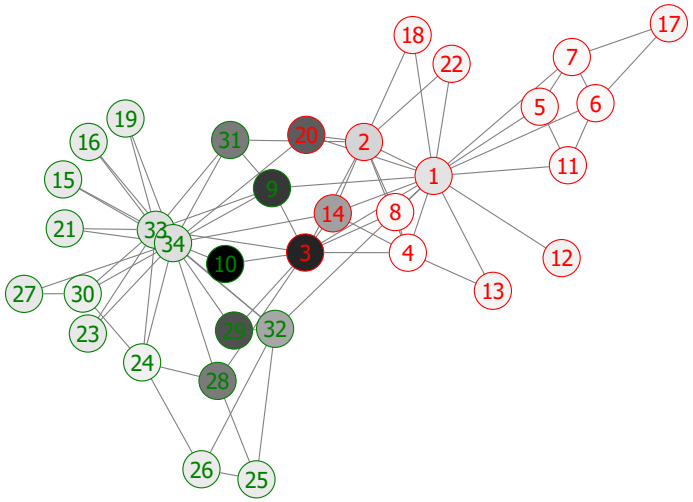
Connected with the sizes of parts of A and compare the distribution of neighbors to the corresponding predictions from the null model. *L^1 norm* $L_1^1(v)$, *L^2 norm* $L_1^2(v)$, *Kullback-Leibler divergence* $\mathrm{kl}_1(v)$, *Hellinger distance* $h_1(v)$.

Our Community-aware features

Community Association Strength

For any $v \in A_i$, we define the *community association strength* as follows:

$$\beta^*(v) = 2\left(\frac{\deg_{A_i}(v)}{\deg(v)} - \lambda\frac{\mathrm{vol}(A_i) - \deg(v)}{\mathrm{vol}(V)}\right).$$



The lower the value of $\beta^*(v)$, the less associated node v with its community is.

Community-aware node features used in our experiments.

abbreviation	symbol	name
CADA	$\mathrm{cd}(v)$	anomaly score CADA
CADA*	$\overline{\mathrm{cd}}(v)$	normalized anomaly score
WMD	$z(v)$	normalized within-module degree
CPC	$p(v)$	participation coefficient
CAS	$\beta^*(v)$	community association strength
CD_L11	$L_1^1(v)$	L^1 norm for the 1st neighbourhood
CD_L21	$L_1^2(v)$	L^2 norm for the 1st neighbourhood
CD_KL1	$\mathrm{kl}_1(v)$	Kullback–Leibler div. 1st neigh.
CD_HD1	$h_1(v)$	Hellinger distance for the 1st neighbourhood
CD_L12	$L_2^1(v)$	L^1 norm for the 2nd neighbourhood
CD_L22	$L_2^2(v)$	L^2 norm for the 2nd neighbourhood
CD_KL2	$\mathrm{kl}_2(v)$	Kullback–Leibler div. for the 2nd neighb.
CD_HD2	$h_2(v)$	Hellinger distance for the 2nd neighbourhood

Experimental data

Syntetic networks ABCD + o

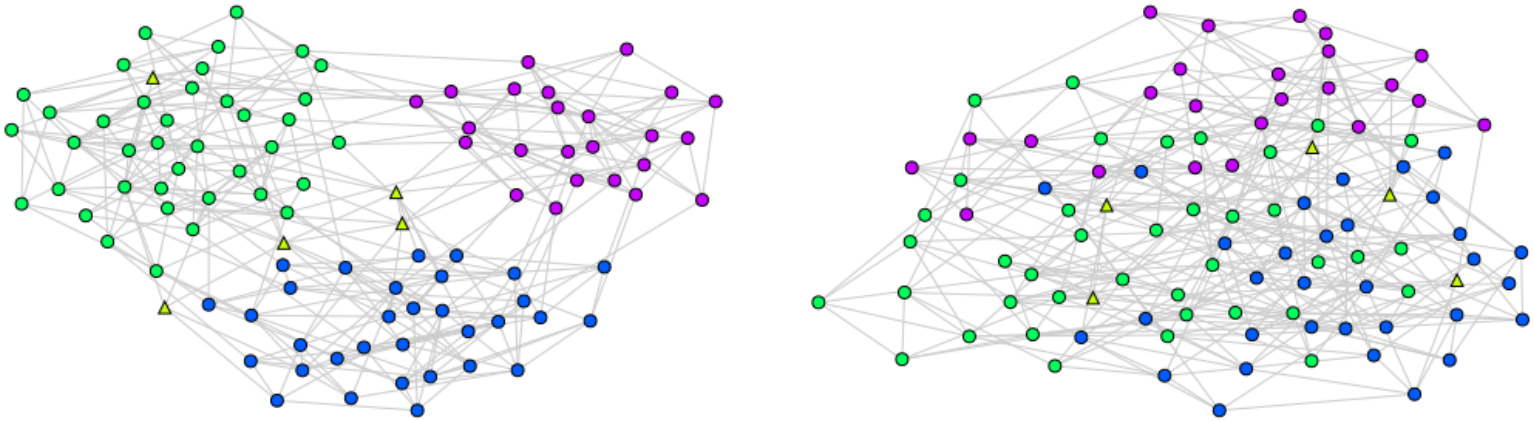
Artificial Benchmark for **C**ommunity **D**etection with **O**utliers
4 networks with different level of noise: $\chi \in \{0.3, 0.4, 0.5, 0.6\}$
N = 10,000 nodes with 1,000 of outliers. The node's degree distr with a power-law with exponent $\gamma = 2.5$ and degrees between 5 and 500. The community's distr with a power-law with exponent $\beta = 1.5$ and size range from 50 to 2,000.

Empirical Graphs

dataset	# of nodes	avg deg	# of clust	target
Reddit	10,980	14.30	12	3.661%
Grid	13,478	2.51	78	0.861%
LastFM	7,624	7.29	28	20.619%
Facebook	22,470	15.20	58	25.670%
Amazon	9,314	37.49	39	8.601%

ABCD+o

The Artificial Benchmark for the Community Detection graph is a random model with community structure and power-law distribution for degrees and community sizes. It has been recently augmented to allow for the generation of outlier nodes (ABCD+o).



ABCD+o graphs with ($\xi = 0.2$, left) and ($\xi = 0.4$, right)

See also: ABCD graph generator in Julia programming language - `https://github.com/bkamins/ABCDGraphGenerator.jl`
B. Kamiński, P. Prałat, F. Théberge: „*Mining Complex Networks*", CRC Press (2022) or *Outliers in the ABCD Random Graph Model with Community Structure (ABCD+o)*.

Experiment 1: Information overlap

The source code allowing for reproduction of all results is available at

https://github.com/sebkaz/BetaStar

This experiment aims to show that classical features cannot entirely explain community-aware features.

Models: Regression kind

Linear regression, Ridge regression, Random forest, XGBoost, Lightgbm.

Measures:

Kendall correlation, spearnman correlation, and R^2 score.

The conclusion is that it is worth including such features in predictive models as they could improve their predictive power. However, this additional information could be noise and not valuable for practice.

Results 1 - ABCD +o

target	$\xi = 0.3$	$\xi = 0.4$	$\xi = 0.5$	$\xi = 0.6$
CADA	0.3305	0.2541	0.2292	0.1766
CADA*	0.3613	0.2877	0.2772	0.1713
CPC	0.3540	0.3568	0.3231	0.3106
CAS	0.4205	0.3584	0.3138	0.2167
CD_L21	0.4539	0.4043	0.3823	0.3313
CD_L22	0.6265	0.5589	0.5009	0.4492
CD_L11	0.5935	0.5571	0.5834	0.5648
CD_L12	0.6503	0.5799	0.5464	0.5188
CD_KL1	0.6991	0.6411	0.5918	0.4929
CD_HD1	0.6809	0.6334	0.6170	0.5584
CD_KL2	0.7453	0.6602	0.6090	0.5471
CD_HD2	0.7546	0.7119	0.6815	0.6352
WMD	0.7670	0.7288	0.6915	0.6387

Results 1 - Empirical graph

target	**Amazon**	**Facebook**	**Grid**	**LastFM**	**Reddit**
CADA	0.5830	0.5666	0.2156	0.4815	0.6826
CADA*	0.6058	0.5828	0.2174	0.5058	0.6867
CPC	0.6338	0.5992	0.2193	0.5175	0.7193
CAS	0.6538	0.6257	0.2999	0.5594	0.7306
CD_L21	0.7052	0.6464	0.3496	0.5698	0.7574
CD_L22	0.7554	0.7355	0.3557	0.6295	0.7941
CD_L11	0.7251	0.7041	0.6978	0.6220	0.7735
CD_L12	0.7794	0.7785	0.6447	0.6884	0.7810
CD_KL1	0.7176	0.7516	0.7394	0.6289	0.7755
CD_HD1	0.7383	0.7482	0.7168	0.6459	0.7853
CD_KL2	0.7706	0.7826	0.7292	0.6853	0.8097
CD_HD2	0.8212	0.8173	0.6930	0.7369	0.8221
WMD	0.8447	0.8456	0.8488	0.8531	0.7638

Experiment 2: one-way predictive power

Target: Verify the usefulness of the community-aware features for the node classification task. For each graph, we build a single model predicting the target variable.

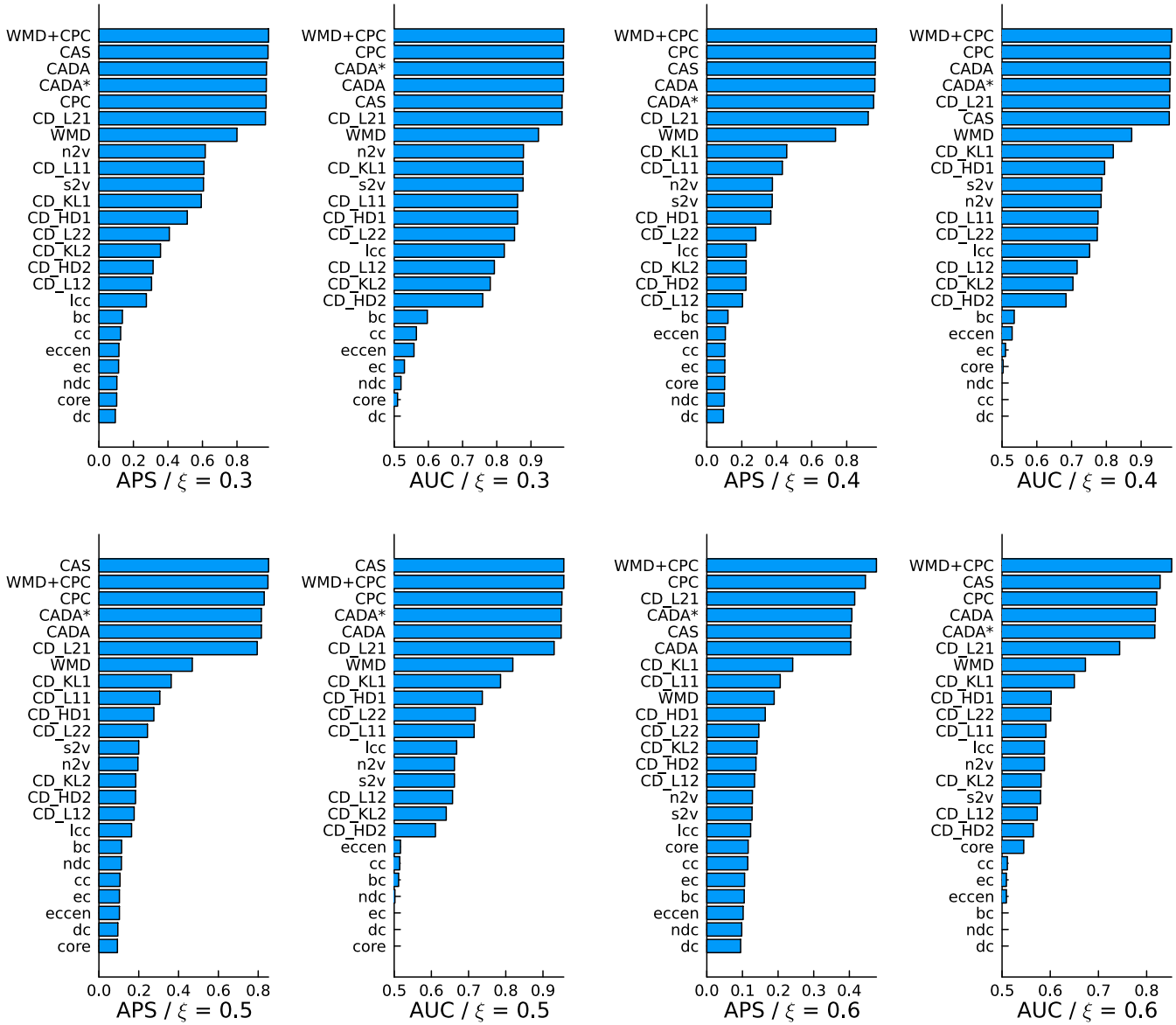
Models: Classification kind

Logistic regression, Random forest, XGBoost, Lightgbm.

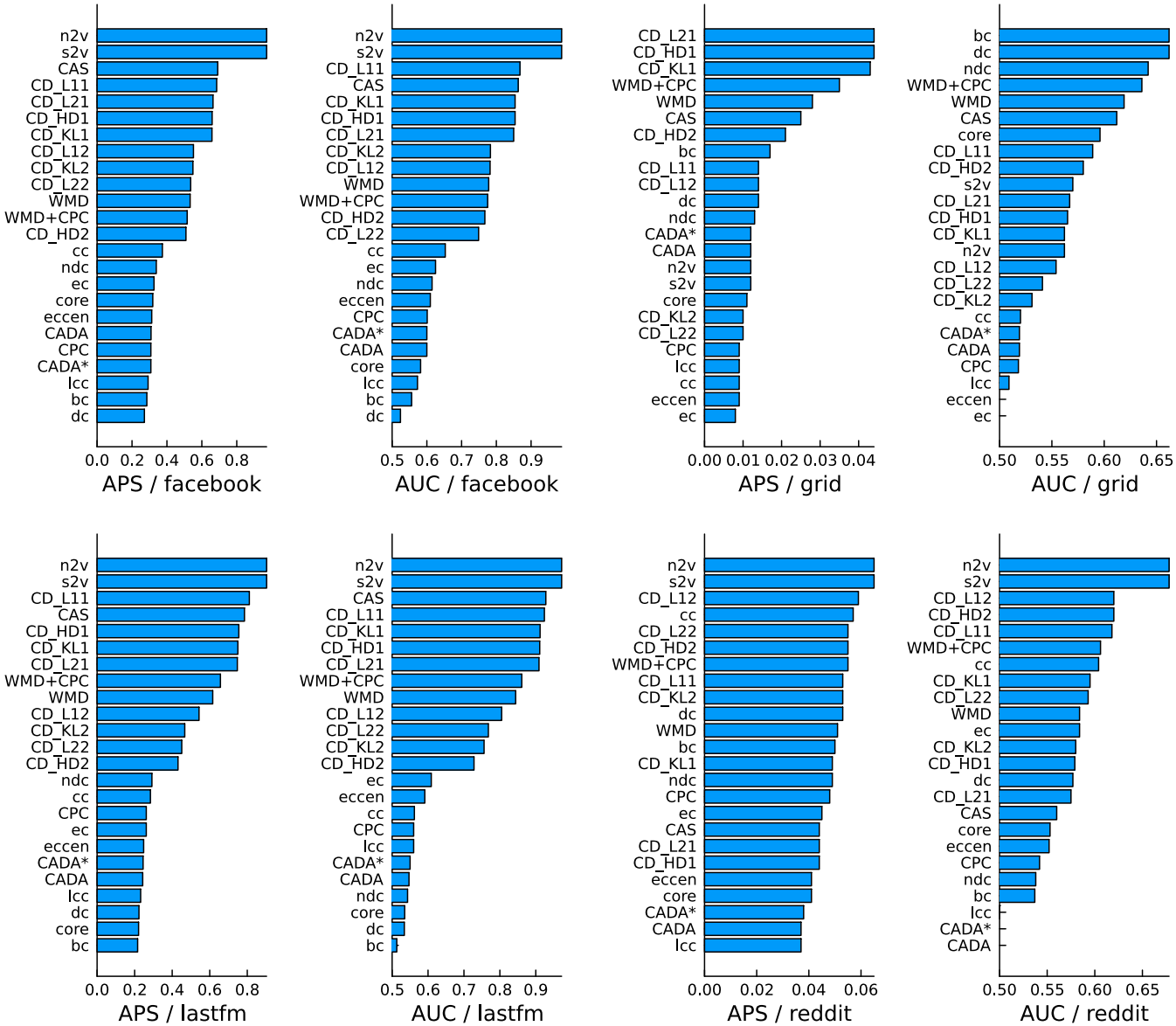
Measures:

ROC AUC score, Average Precision Score.

ABCD + o Results



Empirical Graphs Results



Main results

We verify that:

1. community-aware features contain information that cannot be recovered completely either by classical node features or by node embeddings (both classical as well as structural).
2. there are classes of node prediction problems in which *community-aware features* **have high predictive power**.

Summary

Thanks for Your Attention!

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