

# Outliers detection in complex networks via modularity

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# Outline of talk

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# Motivations

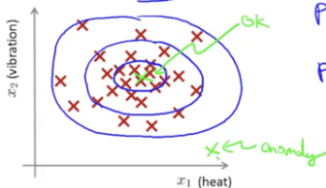
## Anomaly detection

Anomaly detection is a technique used in data analysis for identifying **unexpected behaviour, outliers, rare events, or deviant objects**.  
Offline and online ML, DL, Quantum Computing methodology.

→ Dataset:  $\{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$

→ Is  $x_{test}$  anomalous?

Model  $p(x)$ .

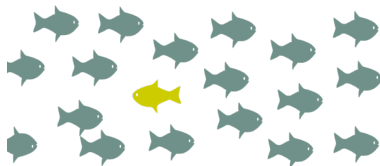


$p(x_{test}) < \varepsilon \rightarrow \text{flag anomaly}$

$p(x_{test}) \geq \varepsilon \rightarrow \text{Ok}$

R. Foorthuis. On the Nature and Types of Anomalies: A Review of Deviations in Data.  
International Journal of Data Science and Analytics, 12(4) (2021)

# Business Motivations



**Fraud Detection**

## Anomaly in business

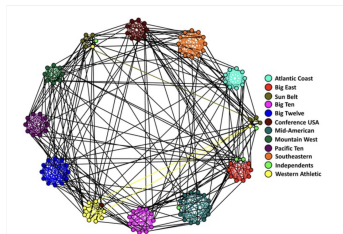
- Unusual Customer Behavioral Patterns
- Fraud detection
- Time series anomalies - stock price, climatology, epidemiology
- Monitoring - cardiac, machine condition, material quality, sales analysis

## Our Case

Outliers detection in complex networks

# Community in complex networks

Being able to identify communities in a network could help us to exploit it more effectively. Community structure plays an important role in understanding the properties of networks.



- social networks - groups by interest
- citation networks - related papers
- web communities - search engine, pages on related topics, fake news detection

# Community in complex network

A network has community structure if its set of nodes can be split into a number of subsets such that each subset is densely internally connected.

Even small number of nodes = a lot of partitions to consider.  
Number of partitions? How to find good partitions?

## First - historical approach

The set of nodes  $C \in V$  forms a **strong community** if each node in  $C$  has more neighbours in  $C$  than outside of  $C$ :  $\deg^{\text{int}}(v) > \deg^{\text{ext}}(v)$ .

$C$  forms a **weak community** if the avg degree inside the community  $C$  (over all nodes in  $C$ ) is larger than the corresponding avg number of neighbours outside of  $C$ .

In this context, **an outlier** could be defined as a node that does not have majority of its neighbours in any of the communities.

# Community detection algorithms, Modularity

Approach using definition of outliers using *strong community* approach is too strict as it typically would lead to too many nodes identified as outliers.

## Modularity

Community detection can be based on modularity function.

**Modularity** for graphs is based on the comparison between the actual density of edges inside a community and the density one would expect to have if the nodes of graph were attached at random (Chung-Lu null-model). For a given partition  $A = \{A_1, A_2, \dots, A_\ell\}$  of  $V$  the modularity function is as follows:

$$q_o(A) = \sum_{i=1}^{\ell} \frac{e(A_i)}{|E|} - \sum_{i=1}^{\ell} \left( \frac{\text{vol}(A_i)}{\text{vol}(V)} \right)^2$$

where  $e(A)$  is the number of edges within set  $A$ ,  $e(A,B)$  is the number of edges between set  $A$  and  $B$ , and  $\text{vol}(A)$  is the sum of degrees of nodes in  $A$ .

# Problems and business case

There are several efficient approaches for community detection that use modularity, the most popular are Louvain, Leiden, and ECG.

Each node is forced to be a member of some community, but in practice some nodes can be outliers (do not fit well into any community) – how to find them?

Such non-fitting nodes can be outliers (do not fit anywhere) or fit several communities (overlapping communities approach)

## Business case

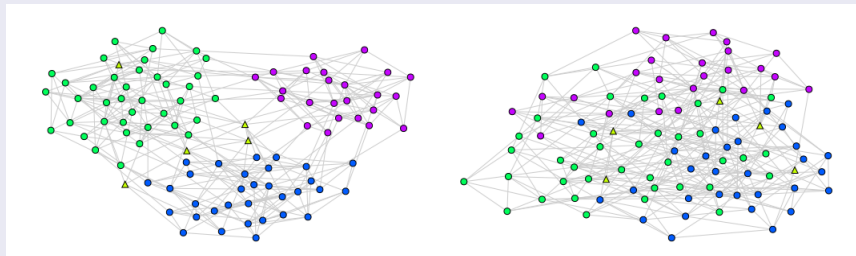
- Tesla fans and BMW fans - but what about fans of all cars? (outlier)
- Barcelona fans Real and Madrid fans - but what about fans of Lewandowski?



# Synthetic networks for Experiments

## ABCD Random Graph Model with community structure

The **A**rtificial **B**enchmark for **C**ommunity **D**etection graph is a random graph model with community structure and power-law distribution for both degrees and community sizes. It has been recently augmented to allow for generation of outlier nodes (ABCD+o).



ABCD+o graphs with ( $\xi = 0.2$ , left) and ( $\xi = 0.4$ , right). The number of outliers is  $s = 5$ .

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)*.

# Real networks for Experiments

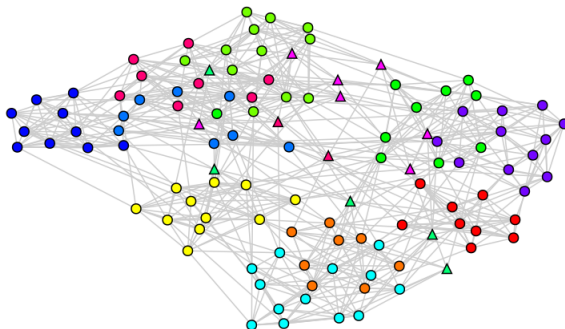


Fig. 3: The College Football Graph; outliers are displayed with triangular shape.

## First attempt

How do adjust modularity to take into account possible outliers?

*We identify nodes that have a distribution of edges approximately evenly spread among all communities and consider them to be outliers not assigned to any community.*

For a given partition  $A = \{A_1, A_2, \dots, A_\ell, O\}$  of  $V$ , where  $O$  is the set of outliers, the *modularity function* is adjusted as follows:

$$q_o(A) = \sum_{A_i \in A} \frac{e(A_i)}{|E|} - \sum_{A_i \in A} \left( \frac{\text{vol}(A_i)}{\text{vol}(V)} \right)^2 - \lambda \left( \frac{e(O)}{|E|} - \left( \frac{\text{vol}(O)}{\text{vol}(V)} \right)^2 \right).$$

where  $\lambda \in \mathbb{R}^+$  is a regularisation parameter.

## Feature (and present) work

- ➊ New definition of the modularity function with outliers.
- ➋ New scalable optimization algorithm for outlier detection.
- ➌ Synthetic networks such as ABCD-o and null models. Investigating experimentally and theoretically their properties.
- ➍ Analyzing real networks and business applications.

If you are interested in this topic, have some suggestions/remarks, then please contact our group.

Thanks for Your Attention!  
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