Selecting Informative Features for Post-Hoc Community Explanation

Sophie Sadler[1], Derek Greene[2,3], and Daniel Archambault[1]

[1] Swansea University, UK
[2] School of Computer Science, University College Dublin, Ireland
[3] Insight Centre for Data Analytics, University College Dublin, Ireland

Abstract. Community finding algorithms are complex, often stochastic algorithms used to detect highly-connected groups of nodes in a graph. As with "black-box" machine learning models, these algorithms typically provide little in the way of explanation or insight into their outputs. In this research paper, inspired by recent work in explainable artificial intelligence (XAI), we look to develop post-hoc explanations for community finding, which are agnostic of the choice of algorithm. Specifically, we propose a new approach to identify features that indicate whether a set of nodes comprises a coherent community or not. We evaluate our methodology, which selects interpretable features from a longlist of candidates, in the context of three well-known community finding algorithms.

Keywords: Network Analysis, Explainability, Community Detection

1 Introduction

Community finding is an important task in network analysis for gaining insight into the network structure. Networks are normally used to represent relational, non-Euclidean data. Data points, known as nodes, are connected by edges which represent relationships between the nodes. Communities are loosely defined as sets of nodes with high connectivity within the community and sparser connections to nodes outside of the community [6]. Identifying communities can provide salient information in many applications, such as public health and computational social science. However, existing community finding algorithms provide little insight beyond the identification of the communities themselves. Since these algorithms are often stochastic, producing potentially different community sets across consecutive runs, and also rarely provide reasoning for these outputs, it remains uncertain as to why the algorithm has identified a certain set of communities. So far, there has been little work to provide further reasoning behind community finding algorithm outputs, which might help an end user to understand the results in a practical context. In particular, community finding algorithms are often used by domain experts with some experience with network analysis, so we try to consider explanations that can assist someone who already has some understanding of complex networks.

In the wider field of machine learning, significant research has been devoted to improving our understanding of model outputs [17]. Since many machine learning algorithms act as a "black box", providing little explanation after training on sometimes millions of parameters, explainability has become imperative to avoiding hidden biases or incorrect assumptions. Although one approach is to develop inherently "transparent" models (i.e., models where the inner workings are easily understood), *post-hoc* explanations have also been developed as an alternative where this is not possible [9, 22]. This involves generating explanations for outputs after the model has already been trained and applied on the data, "without opening the black box" [26]. One such method is to identify important features which a domain expert can easily recognise and interpret [16].

In this paperwe propose a model-agnostic methodology for identifying interpretable features which are able to distinguish "real communities" and "fake communities" (i.e. incoherent communities of poor quality). We conduct a series of experiments[4] using this methodology in conjunction with three well-known community finding algorithms to generate a short list of interpretable features that can be used to explain their outputs. We find that the most informative features across all algorithms were the cut ratio and the internal-external metric, both defined in section 3. As the number of inter-community edges increase, relative betweenness becomes increasingly important. We envision that this insight could be incorporated into future work on generating visual explanations for the outputs of community finding algorithms.

2 Background and Related Work

LIME [22] (Local Interpretable Model-Agnostic Explanations) is a well-known method for post-hoc explanation. The model generates these explanations by perturbing the input data and observing the changes to the output. The relative importance of features is included in the explanation, showing which features contributed to the output. In our work, we adopt a similar use of feature importance to identify the interpretable features which will be of most use in explaining communities. SP-LIME (Submodular Pick LIME) aims to explain the model as a whole, rather than individual outputs. The use of interpretable features in a simpler surrogate model has also been explored by Keane et al. [10], where a complicated neural network is mapped to a simpler case-based reasoning model.

To the best of our knowledge, there has been little work adapting these post-hoc explanation approaches to network analysis, and in particular, community finding. Some work in explainability of unsupervised machine learning has aimed to provide insight into clustering algorithms [18, 15], but not networks or communities. Lanchicinetti et al. [13] compared the performance of community finding algorithms by generating networks using their LFR benchmark [11] with embedded "ground truth" to identify the best performing algorithms. This dataset generation algorithm produces synthetic networks designed to mimic the

[4] Results and implementations for the statistical analysis process are available on OSF: https://osf.io/g4bwt/

structure of real-world networks. One hyperparameter, the mixing parameter μ, is used to determine how well-separated the communities are, as this can vary in real-world networks. At low values of μ, the communities are well-separated, with few edges connecting nodes in different communities. At high values of μ, the communities become harder to identify for the algorithms, as there are more edges connecting nodes in different communities. In our work, we repeat our experiments on networks with different values of μ to see whether the separation of communities affects which features are best able to distinguish between communities and sets of nodes which do not comprise a community.

Despite the lack of existing literature on using features for explainability in a network context, our approach is similar to some previous works which use community quality metrics to evaluate community finding algorithms and their outputs [5, 20, 28]. Some previous literature has also explored the use of network annotations to provide a better understanding of community memberships. In contrast, in our work we focus on scenarios when such additional network metadata in unavailable [19].

Further work by Lee and Archambault [14] compared the performance of well-known community finding algorithms to communities labelled by humans. Their findings were in line with those of Lanchicinetti et al.; the same community finding algorithms performed best on both the human-labelled communities and the LFR benchmark communities. Among these were Infomap [23] and the Louvain algorithm [1], which we include in our analysis later in section 4.

While little work has aimed to explain the communities generated by these algorithms, there has been some exploration into using consecutive runs of stochastic algorithms to generate a more "definitive" consensus clustering for a given network [12]. Other work has explored the consistency of algorithms across several runs [4, 7]. In contrast, in this work we aim to provide interpretable features to explain existing community structure, in a manner that is independent of the choice of algorithm used to detect those communities.

3 Methodology

In order to identify the interpretable features which can distinguish between real communities and other sets of nodes, we propose the following methodology. We perform a comprehensive set of experiments in conjunction with different community finding algorithms, applied to networks with increasing levels of community mixing. Specifically, we make use of the LFR benchmark generator discussed previously in section 2, using different network μ values to vary the level of mixing. For each μ value, a large set of synthetic graphs are generated. Then for each experiment, we run the chosen community finding algorithm on the set of graphs at the current μ value. For each graph, we perform 1000 runs of the algorithm, and obtain the set of unique communities found across these 1000 runs. One node may appear in many different communities within this set, as the community structure may have been identified differently across different runs of the algorithm. However, each community will appear only once in the dataset.

We then calculate our longlist of features for these communities. This gives us our set of candidate features for our examples labelled as "real communities".

Then, we use a rewiring process to adjust the original network structure for each synthetic graph. The feature values are recalculated for each community on the rewired graph, giving us a set of features for our examples labelled as "fake communities". Although the set of nodes in the community remains the same, the structure of the community has changed in the rewiring, resulting in new values for the features. However, due to the one-to-one mapping between the "real community" examples and the "fake community" examples, we can guarantee balanced classes for the classification problem.

Given our labelled examples of "real communities" and "fake communities" generated as described above, in the next step we train a random forest classifier to distinguish between the two classes. The inputs to the classifier are the feature values that as previously calculated. From the resulting random forest model, we can extract permutation importances [2] for each of the input features and perform a statistical analysis to identify which are the most informative.

3.1 Graph Generation

Power analysis is used to determine the number of graphs needed at each of the three μ values (0.2, 0.3 and 0.4) to be 119, which we round up to 120, giving 360 combinations in total. This collection of 120 undirected networks is created using the LFR generator implementation in NetworkX [8], using the following hyperparameters: numbers of nodes 1000; τ_1 and τ_2 3 and 2; average degree 20; maximum degree 50. These values are chosen to match those used in the original LFR benchmark paper [13].

3.2 Community Detection

A key goal of this work is to develop an approach to produce feature-based explanations for communities in a manner that is not tied to a specific community finding algorithm. To generate communities on the collection of all synthetic graphs, we apply a number of popular stochastic community detection algorithms, which are designed for detecting partitions (i.e. non-overlapping communities). Specifically, we employ: Louvain [1], Infomap [23], and Label Propagation (LPA) [21]. We select these algorithms as they have been widely employed in the literature and also since each algorithm differs considerably in terms of the objective which it attempts to optimize. In total, this gives nine experiments (i.e. three algorithms on three μ values). However, we omit LPA on $\mu = 0.4$ since it consistently classifies all nodes in each graph as belonging to a single community.

3.3 Network Features

For the purpose of generating *post-hoc* explanations for communities, we consider a diverse set of features. These have been chosen so as to be interpretable

to domain experts who have some previous experience with network analysis. Therefore, while these features may not be familiar to a layperson, they should be considerably easier for an expert to understand, relative to the specific internal details of the community detection algorithm itself. We consider the simplest features possible, omitting, for example, modularity in favour of those which are easier to understand. The longlist of features chosen for our experiments are as follows:

- *Relative Density*: For a set of nodes V connected by a set of edges E, the density of this set is defined as: $2|E|/(|V|(|V|-1))$. Then the relative density is the density of the community divided by the density of the whole graph.
- *Relative Diameter*: For a set of nodes V, the diameter is the maximum distance between any two nodes. Then the relative diameter is the diameter of the community divided by the diameter of the whole graph.
- *Relative Pathlength*: For a set of nodes V, the average shortest path length is defined as: $\sum_{s,t \in V} d(s,t)/(|V|(|V|-1))$ where $d(s,t)$ is the length of the shortest path from s to t. Then the relative path length is the average shortest path length of the community divided by the average shortest path length of the whole graph.
- *Relative Degree*: For a set of nodes V, the average degree centrality is defined as: $\sum_{i \in V} deg(i)/(|V|(|V|-1))$ where $deg(i)$ is the number of edges adjacent to node i. Then the relative degree is the average degree centrality of the community divided by the average degree centrality of the whole graph.
- *Relative Betweenness*: Let V be a set of nodes of which i, j and k are members. Let $\sigma(j,k)$ be the number of shortest (j,k) paths, and $\sigma(j,k|i)$ be the number of those paths that pass through i. Then the betweenness centrality of node i is given by: $\sum_{j,k \in V} \sigma(j,k|i)/\sigma(j,k)$ Note that if $j = k$, $\sigma(j,k) = 1$ and if either j or $k = i$, then $\sigma(j,k|i) = 0$. Then the relative betweenness is the mean betweenness centrality of the nodes in the community divided by the mean betweenness centrality of the nodes in the whole graph.
- *Relative Closeness*: Let V be a set of nodes of which i and j are members, and let $d(i,j)$ be the length of the shortest path between nodes i and j. Then the closeness centrality of node i is given by: $(|V|-1)/\sum_{j \neq i} d(j,i)$ Then the relative closeness is the mean closeness centrality of the nodes in the community divided by the mean closeness centrality of nodes in the whole graph.
- *Cut Ratio*: Let $w_{ij} = 1$ if nodes i and j share an edge, and $w_{ij} = 0$ if they do not. Then we calculate a cut ratio where set A is the set of nodes in the community, and set B is the set of nodes in the graph *not* in the community, as follows: $1/|A||B| \sum_{i \in A, j \in B} w_{ij}$
- *Internal-External*: Let $w_{ij} = 1$ if nodes i and j share an edge, and $w_{ij} = 0$ if they do not. Then we calculate a measure of internal-external where set A is the set of nodes in the community, set E is the set of edges in the community, and set B is the set of nodes in the graph *not* in the community, as follows: $|E|/(|E| + \sum_{i \in A, j \in B} w_{ij})$

3.4 Graph Rewiring

The longlist of features above is used to calculate features for our set of "real communities", as generated using the algorithms discussed in section 3.2. We subsequently calculate feature values for "fake communities" using a rewiring approach as follows. To rewire each graph, pairs of edges are selected and at random and their endpoints are swapped. For example, for edges (i, j) and (a, b), after swapping the edges will be (i, a) and (j, b), with the original edges removed. A noise level value is multiplied by the total number of nodes in the graph to determine the number of edge swaps. For our experiments, the noise level is set to 0.5. A swapping probability of 0.5 represents a balance between a uniform structure and a random structure in the original discussion of graph rewiring by Watts and Strogatz [27].

3.5 Community Classification

Given our labelled set of "real" and "fake" community feature values generated as per above, we apply a random forest classifier to distinguish between the classes using the following evaluation methodology. We first split the examples into 80% training data and 20% test data. We then train the classifier 50 times on the training data, comprised of 10 repeats of 5-fold cross-validation. A permutation importance is calculated for each node feature after the 50 runs, using the held-out test data. These 50 values then provide us with a distribution of importance values for that feature.

3.6 Statistical Methodology and Pilot Study

In order to confirm the suitability of the above methodology, we ran an initial pilot study on 20 LFR generated networks at each μ value (i.e. 60 networks total). This pilot study was used to determine the behaviour of the underlying phenomena so that we could conduct a proper power analysis. Note that the pilot study networks are not included in the final analysis.

Distributions of each permutation importance for all features were created. We then ran a Shapiro-Wilk test to determine the normality of the phenomena. As the majority of the distributions in the pilot study followed a normal distribution (77%), we took the assumption that the underlying phenomena were normal for our power analysis.

Our statistical methodology was also set before our experiments. Bonferroni-Holm corrections are used in our analysis. The normality of the final permutation importance values on the main experiment are confirmed using a repeat of the Shapiro-Wilk tests, and thus t-tests are used to compare the features. Power analysis was conducted with the following parameters: Cohen's effect size of 0.3, significance level of 0.05, and a power of 0.9. We treat each of the three community finding algorithms independently for analysis and use the pairwise t-tests to identify significantly different pairs of features.

4 Results and Discussion

Results. Following the methodology described in the last section, we now detail the results of the experiment performed on the complete collection of 120 LFR graphs. As discussed, our aim is to identify which of the features listed in section 3.3 have a significantly greater importance than the others in predicting whether a set of nodes represents a "real" or "fake" community. Distributions of permutation importance for the features on each experiment are displayed below in Fig. 1. These distributions are constructed using the 50 permutation importance values calculated during training, as described in section 3.5.

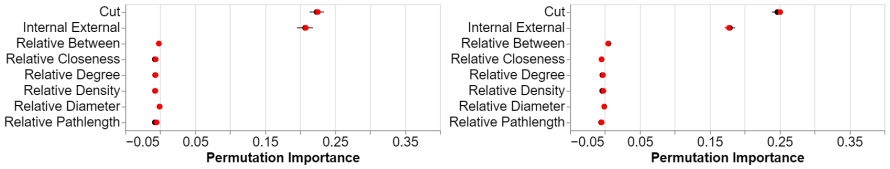
From our experimental results, we see qualitatively that the cut ratio and internal-external metrics are consistently the most important features in distinguishing the "real communities" from the "fake communities". However, as the μ value increases, there is evidence to suggest that the relative betweenness may also have some importance. The Bonferroni-Holm corrected t-tests identified significant differences between these three "important" metrics and all other metrics in the study with the following exceptions:

- Infomap $\mu = 0.2$: relative betweenness compared with relative diameter
- Louvain $\mu = 0.2$: relative betweenness compared with relative diameter
- LPA $\mu = 0.2$: relative betweenness compared with relative degree and relative density

The full set of statistical results is provided in Fig. 2.

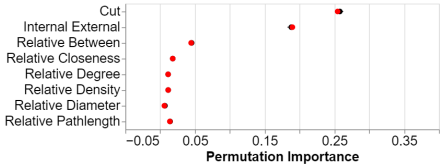
Discussion. The Infomap, Louvain, and LPA algorithms all performed similarly in our experiments, with three features being consistently important for distinguishing the real communities from the fake communities. These were: cut ratio and internal-external for all experiments, with relative betweenness becoming increasingly important with increasing mixing parameter. Thus, when the communities are more clearly defined, or when μ has a low value, more agglomerative features are important for explaining community structure for the set of nodes considered. This finding is not all that surprising as these features are fundamental to the definition of community structure. However, as μ increases and the communities become less well defined, divisive features, such as relative betweenness, become of increasing importance. A possible explanation for this finding is that local connections and neighbours to the node set can be used to understand the community structure when there are few cross community edges, but as these edges increase in prevalence, more global features, such as relative betweenness, become important in explaining community structure.

Surprisingly, despite the fact that the community detection algorithms under consideration involved different objective functions and optimisation strategies, the features that best explained the resulting community structures were the same. This provides evidence that post-hoc explainable network analysis is feasible, independent of the choice of algorithm. In future work, it would be interesting to construct such systems to explain found community structures to end users, rather than domain experts.

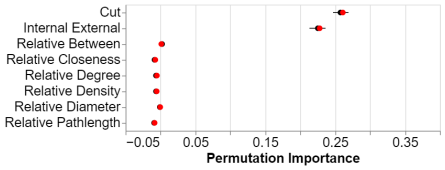


(a) Infomap, $\mu = 0.2$

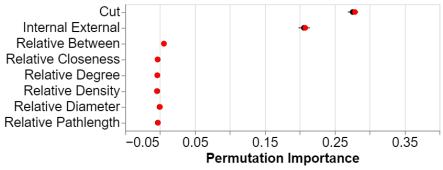
(b) Infomap, $\mu = 0.3$



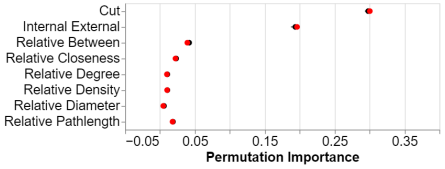
(c) Infomap, $\mu = 0.4$



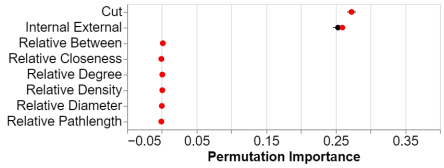
(d) Louvain, $\mu = 0.2$



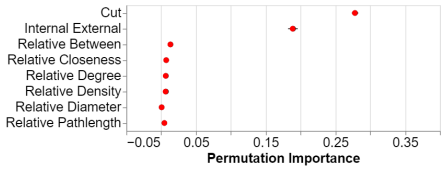
(e) Louvain, $\mu = 0.3$



(f) Louvain, $\mu = 0.4$

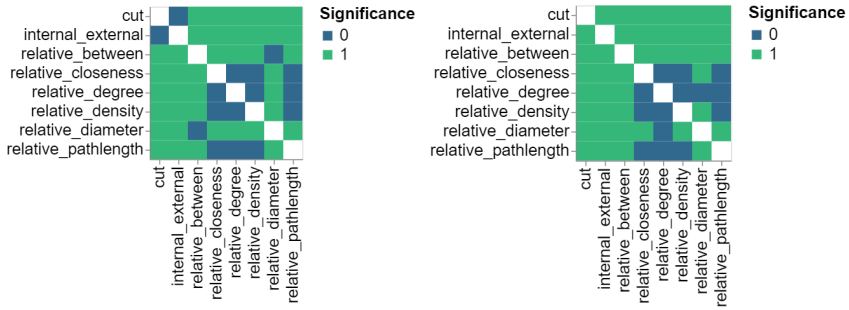


(g) LPA, $\mu = 0.2$

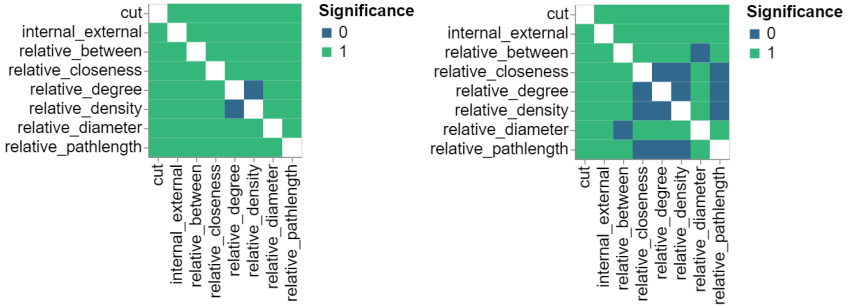


(h) LPA, $\mu = 0.3$

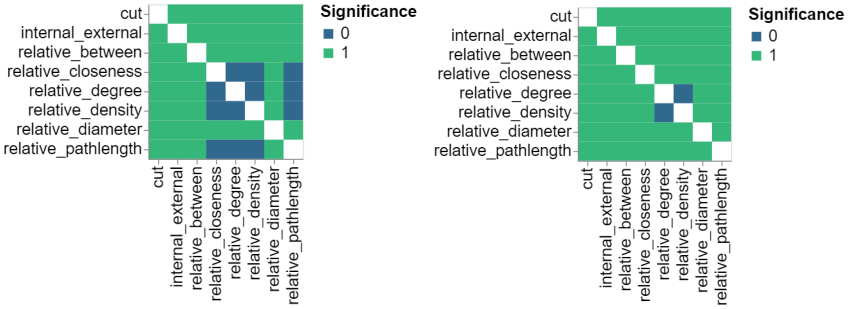
Fig. 1: Results of the community feature experiments. Plots show the permutation importance of the features, across three community detection algorithms and graphs with different levels of community mixing (μ). A mean value is indicated as a black dot and median as a red dot. Lines indicate 95% bootstrapped confidence intervals.



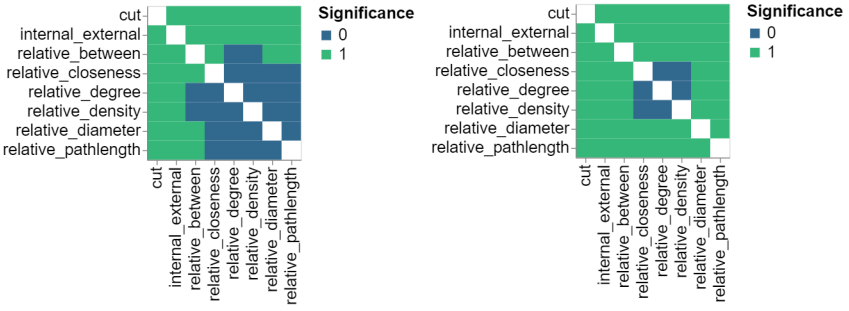
(a) Infomap, $\mu = 0.2$ (b) Infomap, $\mu = 0.3$



(c) Infomap, $\mu = 0.4$ (d) Louvain, $\mu = 0.2$



(e) Louvain, $\mu = 0.3$ (f) Louvain, $\mu = 0.4$



(g) LPA, $\mu = 0.2$ (h) LPA, $\mu = 0.3$

Fig. 2: Results of Bonferroni-Holm corrected pairwise t-tests for different detection algorithms and μ values. Green indicates significance.

5 Conclusion

In this paper, we have presented the methodology and results of an experiment to determine features that can be used to explain detected community structure in networks to a domain expert with some understanding of network analysis. Our experiment tested features which were calculated on sets of nodes that could form a possible community. We find that cut ratio and the internal-external ratio are the most informative features when identifying whether a group of nodes is a community. As the level of mixing between communities increases (i.e. level of inter-community connectivity), relative betweenness increases in importance. This finding was consistent across all community finding algorithms, indicating the potential for using the proposed method to generate model-agnostic post-hoc explanations.

Some areas for future work include: extending this study to real-world network data; further exploration of the effects of the graph rewiring process on the results, e.g. by varying the number of edge swaps; incorporation of localised measures, such as betweenness centrality, into the longlist of features for consideration; and a qualitative assessment of the explainable features using the feedback of domain experts. Ultimately, we would like to perform the necessary HCI and visualisation work to construct explainable network analysis systems that help real users with their tasks. In particular, understanding community structure in social networks is a problem of importance for public health researchers studying social contagion [3, 25] and planning interventions [24] for preventing the spread of harmful behaviour.

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