Benchmarking community detection methods on social media data

Benchmarking the performance of community detection methods on empirical social network data has been identified as critical for improving these methods. In particular, while most current research focuses on detecting communities in data that has been digitally extracted from large social media and telecommunications services, most evaluation of this research is based on small, hand-curated datasets. We argue that these two types of networks differ so significantly that by evaluating algorithms solely on the former, we know little about how well they perform on the latter. To address this problem, we consider the difficulties that arise in constructing benchmarks based on digitally extracted network data, and propose a task-based strategy which we feel addresses these difficulties. To demonstrate that our scheme is effective, we use it to carry out a substantial benchmark based on Facebook data. The benchmark reveals that some of the most popular algorithms fail to detect fine-grained community structure.

Keywords: community detection, benchmarking, evaluation, social networks, datamining, social media data

1. Introduction

Community structure has been identified as playing a key role in the formation and function of many systems, so it comes as no surprise that the topic has received a large amount of attention, with hundreds of papers currently published on the topic every year. However, in the literature on the topic it is commonly observed that although many community detection methods exist, we do not know which ones work best on real data [12, 15, 29, 30].

This problem of evaluation on real data is so acute that, in what has been recognized as the authoritative review on the community detection problem, Fortunato states that our inability to properly benchmark algorithms has led to “a serious limit of the field” and that little is known about which methods perform best in practice [12].

In this paper, we focus on this problem of evaluating community detection methods, focusing on social networks. We first briefly review the history of community detection in order to reveal why the benchmarking and evaluation are currently so problematic. Next we argue that recent attempts to solve the problem of evaluation using large network datasets with “ground truth” data—while a step in the right direction—are flawed because they do not properly deal with the fact that the ground truth data is imperfect and incomplete.

We propose a modified benchmarking workflow which we believe appropriately utilizes an imperfect set of ground truth communities. In this benchmark, we use the communities detected by an algorithm to infer the value of node attributes related to community structure. The inference is done in a machine-learning setting where the community assignment matrix is used as the features associated with each node. The idea is that if the community detection algorithm has done a good job, then a machine learning classifier should be able to use the community assignment matrix to accurately inferring such an attribute. Finally, we run a benchmark using our proposed workflow on forty Facebook datasets. We find that none of the methods we test automatically detect communities at all scales, and the methods become most effective when run many times, each time with a different value for the resolution parameter.
2. A Brief History of Community Detection

We present the following brief history of community detection because we believe the historical trends we highlight are closely related to the currently inadequate standard of evaluation in the field of community detection. In short, we argue that up until the mid-1990s, community detection algorithms were typically run on smaller, hand-curated datasets that were gathered specifically for research. Researchers typically carefully curated these datasets and had well-informed prior knowledge on the community structure. This expert knowledge, based on first-hand experience with the social system from which the data was generated, could be used to set up benchmarks for community detection algorithms. However, since then the focus has shifted to finding communities in larger datasets that are not purpose gathered, but rather digitally extracted, i.e., mined from sources such as log files of web services and mobile communication networks. While the community structure found in these datasets is potentially very different, researchers continue to evaluate their algorithms on the smaller, purpose-gathered datasets. This leaves us ignorant of how well community detection algorithms perform on larger, mined datasets.

With the objective of examining how improvements in community detection methods were evaluated, let us start by examining one of the earliest improvements: the introduction of the adjacency matrix as a means of group detection. The adjacency matrix was meant to improve upon the “sociogram” introduced by Moreno in 1934 [20]. An example of a sociogram is depicted in fig. 1a. While the sociogram as a method for visualization attracted immediate attention (the New York Times described it as a “new science” [4]), laying out nodes and links by hand was criticized as too subjective: “at present, the sociogram must be built by a process of trial and error, which produces the unhappy result that different investigators using the same data build as many different sociograms as there are investigators” [11]. If one looks at fig. 1a, one can observe the grounds for this criticism: not only is it time-consuming to draw such a diagram by hand, but it also seems that the group structure of the social network is not very clear, and that it might be clearer if one had drawn it differently.

In 1946, Forsyth et al. proposed one could represent social networks with an adjacency matrix [11]. The focus of their paper was a procedure for sorting the rows and columns of this matrix in order “to present sociometric data more objectively, and to make possible a more detailed analysis of group structure.” One can argue that the method presented in that paper is the first community detection algorithm. The algorithm orders the entries in an adjacency matrix such that the community structure should be apparent as dense blocks along the diagonal. In fig. 1b, we see the same social network as in fig. 1a, but this time visualized using the technique proposed by Forsyth et al.

For our purposes, the most relevant part of this paper is how Forsyth et al. evaluate how well their method works. Their evaluation can best be described as a sort of informal visual check. They present fig. 1b and assert that the group structure is much clearer than it was when depicted using Moreno’s sociogram method. They outline what they consider the groups to be in fig. 1b using faint dotted lines to draw blocks along the diagonal axis. They simply assert that these boxes represent subgroups, even though these subgroups are not described by Moreno. The important point is that, aside from the visualization, there is no external evidence to support their claim that the subgroups are valid. Thus, the evaluation employed here boils down to visualizing the output of the algorithm and asserting that one can clearly see group structure.

In one sense, this is a poor evaluation: aside from their informal visual check, Forsyth et al. present basically no empirical evidence that their method more objectively detects community structure. A proper empirical evaluation might begin with several networks where the “ground truth” set of communities is known, and then determine whether users of the new method are able to more accurately identify the ground truth set of communities than when they use previously-existing techniques.
(a) One of Moreno’s early sociograms

(b) The same network depicted using Forsyth et al.’s community detection method.

FIG. 1: The first community detection algorithm, introduced by Forsyth et al. in 1946 was supposed to more objectively and clearly display community structure [11]. Because the network used for evaluating the utility of the technique is small and hand-curated, the evaluation was informal, yet adequate.

However, from another perspective, the evaluation is adequate. The researcher who gathered data such as in the example above (in this case H. H. Jennings) typically spends months carrying out surveys on and observing the social system which produces the data. Even before any social network analysis is performed, the researcher has a rich understanding of the social structure that exists among the subjects. In this context, community detection methods are not meant to discover previously unknown structure; rather, they are meant to support, augment, and “make objective” the expert knowledge built up over months of observation and first-hand research.

Over the next fifty years, the datasets used to evaluate community detection algorithms were also generally gathered by experts who had first-hand knowledge of the social system which the dataset covered. Well-known examples include Zachary’s Karate Club [31], Sampson’s Monks [24], and the Southern Women dataset [8]. Through their close observation, the researchers who collected this data were able to group the nodes into communities based on events such as crises or social gatherings. During this time, network datasets tended to be small (with fewer than 500 nodes, and often fewer than 50 nodes) and well-studied (in [13], Freeman synthesizes the findings of 21 methodological studies on the Southern Women’s network alone).

Then, starting in the late 1990s, a new era of work on community detection began. This new era was created in part by a new type of social network data that emerged in the form of digital records such as mobile communication records or data from Facebook. While this new data still represents social networks, it differs from the data that had be analyzed in the previous decades in important ways because it is not collected personally by researchers.

First, the new data sets are typically not collected specifically for the purpose of a scientific study, but rather extracted after the fact from logs or databases. As a result, the data may be messier (e.g., include a majority of users who have very low activity levels) and cover many social contexts for each
user. For example, in most of the datasets gathered up to the mid-1990s, only one social context would be studied, such as activity in a club, at home, or in the workplace. On the other hand, in the more modern datasets, such as Facebook data, social interactions from several social contexts are jumbled together. Another important difference is that the more modern datasets are typically several orders of magnitude larger than the earlier type. Figure 2 displays an example of what we will call a hand-curated network and a digitally extracted network. Finally, whereas the goal of community detection on hand-curated networks was often to make essentially known community structure more objective, the goal on large digitally extracted networks is to uncover completely unknown community structure.

Due to these key differences between the old, hand-curated networks and the new, digitally extracted networks, many new methods for the community detection problem were proposed. The field of community detection enjoyed booming popularity as more physicists, computer scientists, and social scientists developed these new methods. We argue that when modern community detection methods were evaluated on social network data something went wrong: rather than evaluating these new methods on the new datasets for which they were designed, the new methods were often evaluated on the old datasets. [6, 10, 14, 21]¹ Thus, we know that many of the new community detection methods work well on datasets like Zachary’s Karate Club or the Southern Women’s dataset, but we do not know how well they work on larger, digitally extracted datasets, and this is the ignorance that Fortunato described in the excerpt above.

Note that these new methods were evaluated on diverse types of data. For example, the Gene Ontology and other annotation can be used to evaluate the modules found in protein-protein interaction networks [17]; product categorizations can be used to annotate the network of products co-purchased on Amazon.com [30]. See [3] for an example of thorough evaluation on current datasets sets from these datasets.

¹In some of these papers a larger social network was evaluated (such as the co-authorship network on arXiv), but these lacked the ground-truth or meta-data necessary for a proper evaluation. These larger networks were typically employed only for comparing something other than how well the algorithm identifies all relevant community structure, such as which algorithm gets the highest modularity or runs quickest.
and other types of data. Here we consider evaluation only on social network data, i.e., networks in which nodes represent humans and links represent relationships.

There is thus a clear need for benchmarks based on modern, digitally extracted social network datasets, however creating these is not straightforward. Researchers who gather a small dataset by hand for the purpose of studying group behavior can confidently annotate their datasets with the ground truth community structure. On the other hand, with the digitally extracted datasets it is nearly always unclear how exactly one should define a ground-truth set of communities. In some cases, it might not even be clear that such community structure exists in the data at all.

If we are to make progress in detecting community structure in modern datasets, then it is imperative that we design benchmarks based on such data. In the next section, we review recent efforts in this direction and propose how such a benchmark could be created.

3. Evaluation on digitally extracted networks

Recent efforts to benchmark the performance of community detection algorithms can broadly be placed into three categories:

1. **real-world benchmarks**, such as Zachary’s Karate Club, where a dataset based on a social system includes a natural set of ground-truth communities;

2. **synthetic benchmarks**, where data is artificially created according to some model which includes a pre-defined set of ground-truth communities; and

3. **task-oriented benchmarks**, in which communities are used to help complete some task on real-world data, such as graph compression, decentralized routing [26], or attribute inference [19].

The real-world benchmark is ideal, because clear problems exist with the other options. While using synthetic data to benchmark an algorithm is better than nothing, it is unclear how to create synthetic data that is realistic. Thus, even if an algorithm performs well on synthetic data, it may perform poorly on real datasets. The problem with task-oriented benchmarks is that many types of structure may be useful for solving a task, including structures that do not resemble network communities. Thus, the algorithm that performs best on the task-oriented benchmark may not be finding communities at all, but something else, e.g., the clusters identified by block modelling.

Due to these deficiencies, here we focus on the possibility of using real-world benchmark graphs on digitally extracted data. Such a benchmark is typically carried out as in fig. 3. In the last section, we mentioned that many of the smaller, hand-curated datasets include a natural ground truth set of communities which can be used for real-world benchmarks. It is possible to construct this ground-truth because a researcher (or team of researchers) has first-hand experience studying a relatively small social system. For digitally-extracted datasets, no such experts exist, partly because the process of gathering the dataset (which typically involves writing a web crawler or log-file parser) does not involve first-hand contact with a social system, and partly because the dataset is simply too large for any individual to have detailed knowledge of its structure.

Recent attempts to create a ground-truth set of communities for a large, digitally extracted social network typically employ relevant meta-data—perhaps the most significant work in this direction is in two recent papers from Yang and Leskovec [29, 30], who examine the social networks of LiveJournal, Orkut, Friendster, and Ning. Each of these social network datasets includes groups of users explicitly created by users. Another common type of social network data that includes an explicit ground-truth set
of communities is co-authorship networks, where attendance at conferences is used to define the ground truth set of communities.

3.1 Problem: so-called ground truths are incomplete

We now come to this section’s central question: while one can certainly choose to define a ground truth set of communities by using this meta-data, is this a sensible thing to do? In other words: should we punish a community finding algorithm if it’s output does not match such a ground truth? We argue that the ground truth set of communities which can be extracted from such meta-data is likely to be woefully incomplete.

We substantiate this objection with a concrete example based on the Facebook100 dataset, introduced by Traud et al. [27]. We choose our example from this dataset because because it is in many ways an ideal dataset for a community detection benchmark: it comes from Facebook, which at the time the data was collected in 2005, was extremely popular among college students, and thus the data provides thorough coverage of the acquaintanceship among students. Furthermore, as the data was provided directly by Facebook, the dataset is not based on a sample, but rather includes all Facebook friendships. Finally, it includes meta-data based on the profile page of each user that indicates dorm membership, gender, graduation year, and academic major.

As our particular example, we will examine the University of Chicago sub-network, which includes 6,591 nodes and 208,103 undirected edges. This sub-network is chosen because one of the authors has first-hand experience of the social life there as an undergraduate and is even included in the dataset. Furthermore, the residential “houses” are known to be of utmost importance to the social life at the University of Chicago: upon entering the university, every student is required to spend at least one year living in the dormitory system, and the friendships formed in this stage of college—for many students, the first time living away from home—often endure for years. According to the University of Chicago website, “each house represents a tight-knit community of students, resident faculty masters, and residential staff, who live, relax, study, dine together at House Tables, engage, socialize, and learn from each other” [2].

The meta-data does not explicitly indicate that the “dorm” meta-data represents the housing system at the University of
The adjacency matrix of this network is displayed in the top pane of fig. 4. The nodes have been ordered so that all nodes belonging to the same house are adjacent to each other. We can confirm that the house meta-data is indeed relevant for friendships by noting when nodes are arranged in this order.

Chicago, but this is strongly suggested by the data itself, as the number of distinct values corresponds quite closely to the number of houses and fraternity houses. At the time of data collection, the housing system consisted of 10 residence halls (physical buildings) which were further subdivided into 37 houses, which typically represent a physically adjacent wing of a residence hall. House sizes range from 100 to 37 students, with an average size of 70 [1]. Furthermore, there were somewhere between ten and twenty fraternity houses. Thus some of the dorm meta-data may indicate fraternity membership.
dense blocks form on the main diagonal.

However, to return to the central question of this section: should we use these dorms as the ground truth set of communities in a benchmark? In other words: does the grouping of nodes by house correspond to the grouping of network communities that exist in the network? The ordering of nodes in fig. 4 not only blocks nodes by house, but also attempts to highlight any sub or meta-structure.\textsuperscript{3} We can observe that within many of the houses there is clearly defined sub-structure. A few examples of this sub-structure are highlighted in the brown squares in the bottom pane of fig. 4. We can also observe that several of the houses together form one meta-community. An example of this meta-community is highlighted in green in the same image. The twelve houses that belong to this meta-community could represent houses that are physically co-located in the same residence hall.

We do not claim to have found the correct ground truth set of communities in fig. 4; there may be alternative orderings of the adjacency matrix that highlight additional community structure. The point we want to make is that if we were to simply use the houses as ground truth communities in a benchmarking setting, then we would be using, at best, and incomplete ground truth, because it contains neither the sub-structure nor meta-structure that is clearly visible in the adjacency matrix. We also stress that the set of houses alone is not even approximately complete, because while there are only around fifty blue squares, there are several times as many sub-communities visible. Thus, if a community finding algorithm were to find all of the communities that are visible in the adjacency matrix, and then evaluated by measuring how similar those found communities were to the ground truth of houses, the two sets would not be very similar according to several common similarity measures. According such a benchmark, the algorithm would therefore perform poorly, even though in fact it did a good job of detecting communities.

Thus, even though on the face of it the housing meta-data appeared to provide a great ground-truth for a community detection benchmark, it turns out that it is gravely incomplete. We should therefore not build a benchmark based on the house meta-data: the adjacency matrix that highlight additional community structure. The point we want to make is that if we were to simply use the houses as ground truth communities in a benchmarking setting, then we would be using, at best, and incomplete ground truth, because it contains neither the sub-structure nor meta-structure that is clearly visible in the adjacency matrix. We also stress that the set of houses alone is not even approximately complete, because while there are only around fifty blue squares, there are several times as many sub-communities visible. Thus, if a community finding algorithm were to find all of the communities that are visible in the adjacency matrix, and then evaluated by measuring how similar those found communities were to the ground truth of houses, the two sets would not be very similar according to several common similarity measures. According such a benchmark, the algorithm would therefore perform poorly, even though in fact it did a good job of detecting communities.

Thus, even though on the face of it the housing meta-data appeared to provide a great ground-truth for a community detection benchmark, it turns out that it is gravely incomplete. We should therefore not build a benchmark based on the house meta-data: the adjacency matrix that highlight additional community structure. The point we want to make is that if we were to simply use the houses as ground truth communities in a benchmarking setting, then we would be using, at best, and incomplete ground truth, because it contains neither the sub-structure nor meta-structure that is clearly visible in the adjacency matrix. We also stress that the set of houses alone is not even approximately complete, because while there are only around fifty blue squares, there are several times as many sub-communities visible. Thus, if a community finding algorithm were to find all of the communities that are visible in the adjacency matrix, and then evaluated by measuring how similar those found communities were to the ground truth of houses, the two sets would not be very similar according to several common similarity measures. According such a benchmark, the algorithm would therefore perform poorly, even though in fact it did a good job of detecting communities.

3.2 Solution: Measure communities’ relation to meta-data rather than correspondence with it

Returning to the University of Chicago example, we ask: can we create any reasonable benchmark based on the house meta-data? Certainly the houses are related to the community structure, but we are unsure of the nature of this relationship. This relationship could be simple, for example, if a node is a member of a given network community, then it is more likely to be a member of some house. Or this relationship

\textsuperscript{3}To highlight sub-structure within each house, we performed the following steps: we first extracted the sub-graph induced by each house (i.e., the edges contained in each blue-square in fig. 4) and then ran a community detection method on that sub-graph (we used the Louvain method of modularity maximization \cite{5}, but many non-overlapping community detection algorithms would also have been appropriate). We then arranged the nodes within each house block-wise by the network communities found in that house’s sub-graph. To highlight meta-structure between dorms, we created a meta-graph by turning each house into one node in the meta-graph, and weighted the edges between nodes in the meta-graph by the total number of edges which connected houses in the original graph. We then found communities on the meta-graph using the same method. Finally, we ordered the houses in fig. 4 block-wise by the sets of houses that were identified as belonging to the same meta-community.
could be more complex, for example, if a node is a member of a certain set of network communities and at the same time not a member of some other set of network communities, then there is a high probability of belonging to a certain house. Due to these possibilities, while we might know that certain meta-data (such as the housing-meta data) is closely related to community structure, we often do not know the exact nature of this relationship.

Thus, we would like to create a benchmarking scheme which allows for a flexible relationship between network communities and meta-data that we believe is closely related to community structure. In such a scheme, we do not want to assume we have knowledge of a complete ground-truth set of communities.

We observe that the objective of machine learning is to come up with models that flexibly capture the relationship between a set of features and some target attribute. In fact, machine learning models are designed to be used precisely in situations where the relationship between the features and the target attribute is complex and unknown. Building on this observation, we propose that one valid way to incorporate meta-data into a benchmarking scheme is to treat the meta-data as a node attribute whose value can be more easily inferred with a good set of network communities. In a way, we shift from a ground-truth based benchmark to a task-oriented benchmark, where the task is to infer missing meta-data.

The benchmarking procedure that we propose is illustrated in fig. 5. The first step is to detect communities with the algorithm which is being benchmarked. These detected communities are used to build a community assignment matrix, where each row corresponds to a node, and each column corresponds to a detected community. The values in this matrix are either one or zero—a value of one at position \((i, j)\) indicates that node \(i\) is a member of community \(j\). The meta-data is used to label each node’s class. With the community-assignment matrix as the feature matrix, and the meta-data as the labels, we can then train a machine learning model in the usual manner, and use 10-fold cross validation to measure the accuracy of the model.

The accuracy indicates how well the communities as features allow the meta-data to be inferred—the higher the accuracy, the better the communities. This makes sense if we assume that the community structure is closely related to the meta-data. However, there are some important conceptual objections one could raise against this benchmarking scheme. First, all sorts of network features might be useful for inferring missing meta-data, so the algorithm that performs best in such a benchmark may not even be detecting network communities at all. Second, if a community detection algorithm produces several
irrelevant communities, then many machine learning models are clever enough to simply ignore these. Thus, a community detection algorithm will not necessarily be punished for producing a large set of bogus communities. In fact, if one had infinite computing time and an ideal machine learning model, then a trivial community detection algorithm would always obtain the top score: the algorithm that produces all possible communities. Given all these communities, the ideal machine learning model would discover which subset of communities allowed the most accurate inference of the meta-data.

We point out that any benchmarking scheme which is based on an incomplete ground-truth will have the same problems, because given a detected community that does not correspond to anything in the incomplete ground truth, one cannot say whether the community is invalid or whether it is valid but not included in the ground truth.

Furthermore, while these objections are valid and need to be kept in mind when interpreting results, we believe they can be addressed. One can ensure that the algorithm in question does in fact detect network communities and that it does not detect bogus communities by running it on synthetic benchmark networks with clear community structure in which the ground-truth is complete. In this context, the synthetic benchmark networks are not used to determine which community detection algorithm is the best, but rather as a sort of sanity check to make sure that the algorithm in question is in fact a community detection algorithm and does not detect a large number of bogus communities. Thus, the synthetic network used should have clear community structure that is relatively easy to detect.

One might argue that since the goal here is simply to measure how related the community assignment matrix is to some meta-data, a simpler approach would be to use some measure of mutual information between the community assignment matrix and the meta-data. If the community structure were a non-overlapping partition, then this task would be straightforward—one could use the normalized mutual information as defined in [7]. Because nodes can belong to several communities, this measurement becomes more difficult. While the mutual information of groupings (as opposed to partitions) has been defined (see [18] for an overview), these definitions do not take interactions between community membership into account. Because we believe that in social systems the relation between community membership and some target attribute may be more complex than allowed for by these measure of mutual information, we choose instead to use machine learning models to measure this relation, as these strive to form more flexible hypotheses about how a feature space is related to some target attribute.

We began this section by defining three types of benchmarks used to measure the performance of community detection algorithms, and then explained why one would ideally use real-world networks in which the complete ground truth was known. We then argued that the meta-data associated with digitally-extracted networks is unfortunately likely to be incomplete, and therefore inappropriate for real-world benchmarks. Thus, while in theory we would like to use real-world data with complete ground truths, in practice no such datasets exist. Finally, we proposed an alternative benchmarking scheme which includes both a task-oriented component and a “sanity check” component based on synthetic data. In the next section, we carry out the proposed task-oriented benchmark in order to provide a concrete example of what we have in mind, and to demonstrate that such a benchmarking scheme can reveal insight into the behavior into the community detection algorithms.

4. Illustrative example: a benchmark based on Facebook data

The primary purpose of this section is to flesh out the benchmarking procedure outlined in fig. 5. Along the way we also uncover problematic behavior exhibited by a few community detection algorithms; for example, the Louvain and InfoMap methods seem to detect community structure only at a very coarse level, even if hierarchical versions of these algorithms are used.
Data and experiment design. First, a word on the data. In the last section, we illustrated an example with a Facebook network representing acquaintanceships at the University of Chicago. As we mentioned above, this network came from a larger dataset, the Facebook100 dataset from Traud et al. [27], which includes Facebook data on 100 collegiate networks; these 100 networks are the data used here. These networks range in size from 769 nodes and 17k edges to 36k nodes and 1.6m edges. The data has all of the desirable characteristics described above, for example, it comes directly from Facebook and is not sampled. Furthermore, the dataset includes node attribute information on five attributes: gender, year of graduation, dormitory (as used in the last section), academic major, and high school. Note that no edges exist between members of different networks, and that each network is treated independently of the other networks.

Traud et al. found that two of these attributes had a close relationship with community structure: year of graduation and dorm. Our benchmark will therefore contain two separate components: one in which communities are used to infer dorm membership, and the other in which they are used to infer year of graduation. For each combination of network and algorithm, we first detect communities and use them to build a community assignment matrix. Next, for each attribute, we use ten-fold cross validation to measure how well a classifier can infer the attribute based on the community assignment matrix. We measure a classifier’s accuracy by simply calculating the percentage of time that a classifier correctly infers the attribute.

We reiterate that the assumption underlying benchmarks is that each of these attributes is closely related to community structure, and so as the community assignment matrix tends to improve and more closely resemble the unknown ground truth, this matrix will allow a machine learning classifier to more accurate inference of missing attributes.

Classifier. Some of the community detection methods benchmarked here detect thousands of communities on these networks, so it is essential that the classifier used performs well in situations with thousands of features, otherwise our benchmark may be biased against methods which detect many communities. After experimenting with several classifiers and feature selection schemes, we found that an ensemble method called stochastic gradient boosting both performed best and was least sensitive to large numbers of communities. In particular, we use the implementation provided in the Python package scikit-learn [22], with the learning rate set to 0.005 and the number of trees set to 1000.

Community detection methods tested. We benchmark four community detection algorithms: the Louvain method of modularity maximization [5], the InfoMap method of map equation maximization [23], the Link Community method (LC) [3], and the Greedy Clique Expansion algorithm (GCE) [16]. We choose the Louvain method and InfoMap because they are perhaps the two currently most popular methods of community detection. We include the Link Community method and GCE because they both claim to handle the case of overlapping communities particularly well, and we have reason to believe that in the Facebook data most nodes could belong to multiple communities.

We used the author’s implementation of the Louvain method, which allows for both flat and hierar-
chical partitions, both of which will be considered below. We also used the author’s implementation of the InfoMap algorithm\(^7\) presented in [23], which is designed to detect hierarchical community structure. Likewise, we used the author’s C++ implementation of LC, which can detect either a flat or hierarchical clustering, both of which will be tested below.\(^8\) Because LC often found vast numbers of extremely small communities, we removed all communities containing fewer than four nodes or three edges. For GCE, we used the author’s implementation,\(^9\) and set the value of the resolution parameter \(\alpha\) to 1.5, as this value was recommended for the Facebook data in previous work. We should note that because GCE has a resolution that has been tuned to this type of data, it has an unfair advantage over the other algorithms; however, in the latter part of this section we also try to optimally tune the resolution parameters of the other methods.

**Results.** Results are presented in table 1. Note that training the classifier is computationally expensive, and for this reason we run our benchmark on only the forty smallest universities. Furthermore, rather than carrying out the evaluation of accuracy on all ten folds of the cross-validation scheme, we use only three.\(^10\) Thus, for each combination of community detection method and attribute, we detected communities on the forty smallest networks, then trained classifiers to infer the attribute on three folds, yielding a total of 120 classifiers. The “mean accuracy” columns presented in tables 1 to 3 therefore indicate the average accuracy obtained by these 120 classifiers. We also show the distribution of these 120 accuracies with a histogram.

Turning to the results, we see that GCE has the best performance on inferring values for both the dorm and year attributes; in particular, it performs substantially better than the other methods on the dorm inference task. We observe that the Louvain and InfoMap methods detected a smaller number of larger communities, whereas GCE tended to find more and smaller communities. We believe that the Louvain and InfoMap methods performed poorly because they missed the fine-grained community

---

\(^7\)https://www.tp.umu.se/~rosval1/code.html

\(^8\)https://github.com/bagrow/linkcomm

\(^9\)https://sites.google.com/site/greedycliqueexpansion/

\(^10\)Even so, our benchmark scheme took months to carry out on a machine with 32 cores—it required us to train 2400 classifiers (ten community detection methods, three folds, forty universities, two attributes). Some of these classifiers were slow to train because they needed to be trained on more than ten thousand features (a variation of the link-clustering method labeled below as linkClusterCombined found by far the most communities and therefore the classifiers trained on these communities took up most of the CPU time).
| Louvain Parameters | Dorm Accuracies | Year Accuracies | UChicago Stats |
|--------------------|----------------|----------------|----------------|
|                    | Markov Time | Multi-level | Histogram | Mean | Histogram | Mean | Median Smallest | # Comms |
| 1.0                | ✓            |            | 25.4      |      | 60.0      |      | 1016.0          | 27      |
| 1.0                | ✓            |            | 27.2      |      | 61.1      |      | 923.0           | 97      |
| 0.5                | ✓            |            | 33.5      |      | 62.2      |      | 231.0           | 151     |
| 0.2                | ✓            |            | 42.7      |      | 63.5      |      | 93.0            | 254     |

Table 2: Performance of variations of the Louvain method of modularity maximization—the left-most column indicates the value of "Markov time" used. Markov time is a resolution parameter; when set to 1.0, the original definition of modularity is recovered. The second column indicates whether a flat cut was used on the dendrogram, or all inner nodes of the dendrogram were used as communities.

structure.

We can demonstrate this point by returning to the example of the University of Chicago that was presented in fig. 4. The "UChicago Stats" section of the table indicates the number of communities found on the University of Chicago’s Facebook network—this is helpful because we have already seen from the adjacency matrix in fig. 4 that this network contains at least several dozen (perhaps hundreds) of network communities, and that nodes appear to belong to both small and large communities. To calculate the “median smallest” column, for each node we first recorded the size of the smallest community it belonged to, and then we took the median of this distribution. This column indicates that the Louvain and InfoMap methods failed to place most nodes into any small communities, whereas GCE did typically place nodes into smaller communities. We would expect these fine-grained communities to be useful for inferring dorm attribute, because the partition formed by dorm membership includes more and smaller groups than the one formed by the year attribute.

The LC method behaved strangely on the UChicago network and several of the other networks: the vast majority of the communities found were singleton communities (containing one edge and two nodes), and only ten of the detected communities contained four or more nodes. It appears that the cut made in the dendrogram produced by this network was made at too low of a level—we will try to remedy this problem below by making cuts at several levels and combining the communities from each cut. First, we will see if we can improve the performance of the Louvain method by tuning it to detect finer-scale structure.

The Louvain method and multi-scale community detection. To further investigate whether the Louvain method’s poor performance is due to missing communities at the smallest scale, we perform additional experiments. The scores for the Louvain method presented in table 1 are based on the optimal flat partitioning. However, as the Louvain method is based on an agglomerative, hierarchical clustering, one can also include communities from all levels of the dendrogram, not just the flat cut which optimizes modularity. Blondel et al., the authors of the Louvain method [5], claim that the method “unfolds a complete hierarchical community structure for the network,” which suggests that the algorithm should detect community structures on all scales. In the second row of table 2, we present the results when communities detected at all levels are used. We note that the accuracy increases slightly, and that the number of communities found increases—for example, on the University of Chicago network, the number of communities increased from 27 to 97.

The findings of [9] indicate that to find community structure at all resolutions, the very definition
of modularity should be parameterized with a parameter called “Markov time.” We test this claim by checking whether such a parameterized version of modularity can yield fine-grained communities that improve accuracy. We use the implementation by Renault Lambiotte, which is fortunately based on the very same implementation of the Louvain method and so allows for direct comparison.\footnote{Available at http://www.lambiotte.be/codes.html} We set the resolution parameter to 0.5 and 0.2, which are values that should detect community structure on a smaller scale than the unparameterized version of modularity used above, which implicitly sets this value to 1.0. For each of these values, we extract all communities from the dendrogram, as described in the last paragraph. We observe that when the Markov time is decreased, the number of communities detected increases and the accuracy increases significantly for the dorm attribute. As the dorm attribute is more closely associated with finer-scale community structure, this indicates that the resolution parameter does indeed help to find community structure on a smaller scale.

This finding suggests that when modularity maximization techniques are used, then in order to find community structure at smaller scales, it is not enough simply to use a hierarchical clustering technique and make cuts at all levels in the resulting dendrogram. Rather, the very definition of modularity itself must be parameterized with a resolution parameter. While there is much theoretical literature on “resolution limit” inherent in modularity, here we find strong empirical evidence of this limit.

Our findings here also place the results of Traud et al. [27] into doubt. They analyzed the community structure in the Facebook\textsuperscript{100} network using a modularity maximization technique, but paid no consideration to the resolution limit. Traud et al. found that in larger universities, year of graduation was more relevant for community structure than dormitory assignment. Our results indicate that this finding is likely not inherent in the data, but rather due to a limitation of modularity maximization techniques: in larger networks, a naïve application of these techniques does not detect finer-grained communities.

The importance of a resolution parameter for modularity raises the question of whether InfoMap could also perform better if its objective function, the Map Equation, were parameterized with a resolution parameter. As mentioned above, while the implementation of InfoMap that we used is designed to detect community structure at all relevant resolutions, tended to detect only larger communities. Along the lines of the parameterized definition of modularity discussed above, recent work in [25] has parameterized the Map Equation (which InfoMap optimizes) with a resolution parameter by modifying the Markov time used to compute the stationary distribution of the random walk. We tried to use their implementation, but encountered unexpected behavior and results that were worse than with the unparameterized InfoMap.\footnote{In particular, when the resolution parameter of the parameterized InfoMap is set to 1.0, then the original InfoMap should be recovered, but this was not the case.} We believe that these results are related to implementation rather than the conceptual modifications, and therefore do not report these results.

Combining multiple runs to find structure at all scales. Leaving InfoMap aside, each of the three other algorithms has a resolution parameter: for the Louvain method, we have the Markov time, for the LC method we have the threshold at which to cut the hierarchical clustering of edges, and GCE has a parameter \(\alpha\) which is built into its local objective function. In order to detect communities at all scales, one could run the algorithm multiple times using different values for the resolution parameter, and then combine the results. In our final experiment, we check whether such a procedure increases the performance on the benchmark. We combine runs of the Louvain method where the Markov time is set to \(t = 0.1, 0.2, \ldots, 1.0\) and ; we combine runs of LC where the threshold for the cut is set to each integer-valued percentage point between 1 and 100, and we combine runs of GCE where \(\alpha\) is set to 0.8,
When combining several runs of a community detection algorithm, the resulting set of communities can contain a very large set of near-duplicate communities. For example, in a single run, the LC method finds over 100,000 communities on some of the Facebook100 networks, so when several runs are combined, this number can reach into the millions. The vast majority of these millions of communities are near-duplicates of other communities, an undesirable property in most settings, and one which in the current context makes the training of the classifier computationally expensive. When we combine several runs of an algorithm, we therefore remove the near duplicates by following the procedure outlined in section 2 of [16], setting $\varepsilon$ to 0.5; this technique basically removes communities that have a Jaccard similarity of greater than 0.5 with any communities of equal or lesser size.

The results of this final experiment are displayed in table 3. We see that each method has benefitted by combining the results of multiple runs at different settings of the resolution parameter.

We now wrap up this demonstration benchmark with a summary of our findings. Many community detection techniques strive to be parameter free so that they can automatically detect communities without requiring a user to experiment with different parameter values [12]. While this is a worthy goal, the results of this section indicate that to achieve good performance, one must tweak the resolution parameter of every method tested here. If we compare the results in table 1 with those in table 3, we see that if one simply trusts the algorithm to automatically set the resolution parameter, then the method may in practice struggle to find structure at all relevant levels. For example, the naive application of the Louvain method produces a set of communities which allow a classifier to infer the dorm attribute with an accuracy of only 25.6%, whereas by combining multiple runs with different values of the Markov time parameter, one can obtain an accuracy of 50.4%. This dramatic increase in performance (as well as our analysis above) indicates that the naive application of the algorithm failed to detect much of the finer-grained community structure.

### 5. Conclusion

In section 2, we distinguished between digitally extracted networks and small, hand-curated networks, and we argued that these two types of data differ in important ways. We also pointed out that although the recent wave of community detection methods are supposed to work on digitally extracted networks, in practice the only real data they are tested on are small, hand-curated networks. As a result, we are unaware of whether these methods work on digitally extracted networks. This situation is caused in large part by the lack of digitally extracted networks with acceptable ground-truth data; indeed, in section 3 we showed that even in cases where it appears that one may have a reasonable ground truth...
set of communities, this ground truth is likely to be quite incomplete, and therefore unsuitable for a straightforward benchmark such as the one depicted in fig. 3. In that section we also proposed an alternative benchmarking scheme that is appropriate for the case where one has only an incomplete ground-truth. Finally, in section 4 we employed this alternative benchmarking scheme.

The results in section 4 demonstrate how the inference-based benchmarking scheme we proposed in section 3 can reveal limitations of community finding algorithms. The benchmarks indicate that some of the most popular community detection methods struggle to detect communities at smaller scales. We note that this problem did not emerge when these methods were benchmarked on small, hand-curated networks, and this suggests that we cannot assume that just because a community detection method works well on small, hand-curated networks like Zachary’s Karate Club, it does not mean it will work as well on digitally-extracted networks.

An unfortunate drawback of the benchmarking approach presented here is its complexity. The benchmarking workflow involves components that are not directly related to community detection—such as classifiers—which add extra parameters whose values must be set with care. While this complexity is unfortunate, we feel that the simpler approach of treating meta-data as if it contained a complete ground truth, as in [29, 30], is even more problematic because it may unfairly punish a community algorithm for detecting a valid network community that does not exist in an incomplete ground truth.

One benefit of this benchmarking approach is that it indicates a practical problem for which network communities are useful. We can confirm that network communities are in fact useful for inferring missing attribute values.13

While it is not the primary concern of this paper and so we will not go into great detail on the matter, we note that we also conducted further experiments in which the goal was not to benchmark community detection algorithms, but rather to infer attribute values as accurately as possible. In these experiments we included two additional types of node features that one would almost certainly use in practice. First, each node had features indicating its attributes such as gender, academic major, year of graduation, and dorm (of course, we left out the attribute which we were trying to infer). Second, each node had features indicating the percentage of its friends who had each attribute value; e.g., the percentage of friends that were male or female, and the percentage of friends in each possible academic major. We found that these two simple feature types allowed for more accurate classification than network communities. When we combined all three feature types (i.e., each node’s attributes, its friends attributes, and the network communities to which it belonged), the accuracy improved only slightly (by less than 1%) over the case where we left out the network communities altogether.

Thus, if one were trying to infer the missing attribute values in the Facebook100 dataset, one could obtain quite good results even if one ignored network communities altogether and use simpler features based simply on node attributes the distribution of these attributes in each node’s egocentric network. While this may be a rather gloomy finding for champions of community detection, we note that this finding does not indicate the network communities are useless, but rather that in the particular case of the Facebook100 dataset, these two other features simply happen to contain information which is very useful for inferring missing attribute values.

The accuracy with which we could infer missing node attributes should be taken with a grain of salt. In our scheme, we measured this accuracy by holding out data from nodes whose labels were known, whereas in practice, one would want to infer values for nodes with unknown labels. It could be these nodes with missing labels differ from the nodes with known labels, and as a result, the accuracy of inferring their labels might differ. Because our objective was simply to measure how related community structure is to meta-data—and not to accurately measure how well we can infer missing data in practice—this limitation is not problematic for the work presented here, but should be borne in mind by those who are interested in attribute inference for its own sake.
We conclude by noting that while the benchmarking here was based on the task of inferring missing node attributes that we believe to be closely related to community structure, one could construct conceptually similar benchmarks based on different tasks. One natural example would be to use network communities to perform supervised link prediction; this is a natural fit because presumably the processes responsible for link formation are closely related to the processes which form network communities.

Funding
This work is supported by Science Foundation Ireland under grant no. 08/SRC/I1407, Clique: Graph and Network Analysis Cluster.

References
[1] (2004) University of Chicago House system. http://web.archive.org/web/20041031080505/http://www.rh.uchicago.edu/hds/housing/. Accessed: 28/12/2012.
[2] (2012) Announcing New Residence Hall and Dining Commons. http://csi.uchicago.edu/feature/announcing-new-residence-hall-and-dining-commons. Accessed: 28/12/2012.
[3] Ahn, Y., Bagrow, J. & Lehmann, S. (2010) Link communities reveal multiscale complexity in networks. Nature, 466(7307), 761–764.
[4] Author, U. (1933) Emotions Mapped by New Geography. The New York Times.
[5] Blondel, V., Guillaume, J., Lambiotte, R. & Lefebvre, E. (2008) Fast unfolding of communities in large networks. Journal of Statistical Mechanics: Theory and Experiment, 2008(10), P10008.
[6] Clauset, A., Moore, C. & Newman, M. (2007) Structural inference of hierarchies in networks. Statistical network analysis: models, issues, and new directions, pages 1–13.
[7] Danon, L., Guilera, A. D., Duch, J. & Arenas, A. (2005) Comparing community structure identification. Journal of Statistical Mechanics: Theory and Experiment, 2005(9), P09008–09008.
[8] Davis, A., Gardner, B. & Gardner, M. (1941) Deep south. University of Chicago Press Chicago.
[9] Delvenne, J., Yaliraki, S. & Barahona, M. (2010) Stability of graph communities across time scales. Proceedings of the National Academy of Sciences, 107(29), 12755–12760.
[10] Duch, J. & Arenas, A. (2005) Community detection in complex networks using extremal optimization. Physical review E, 72(2), 027104.
[11] Forsyth, E. & Katz, L. (1946) A Matrix Approach to the Analysis of Sociometric Data: Preliminary Report. Sociometry, 9(4), pp. 340–347.
[12] Fortunato, S. (2010) Community detection in graphs. Physics Reports, 486(3-5), 75–174.
[13] Freeman, L. C. (2003) Finding social groups: A meta-analysis of the southern women data. In Dynamic Social Network Modeling and Analysis. The National Academies, pages 39–97. Press.
[14] Girvan, M. & Newman, M. (2002) Community structure in social and biological networks. *Proceedings of the National Academy of Sciences*, **99**(12), 7821–7826.

[15] Lancichinetti, A., Kivelä, M., Saramäki, J. & Fortunato, S. (2010) Characterizing the community structure of complex networks. *PLoS One*, **5**(8), e11976.

[16] Lee, C., Reid, F., McDaid, A. & Hurley, N. (2010) Detecting highly overlapping community structure by greedy clique expansion. *SNA-KDD 2010*, page 11.

[17] Marras, E., Travaglione, A., Chaurasia, G., Futschik, M. & Capobianco, E. (2010) Inferring modules from human protein interactome classes. *BMC systems biology*, **4**(1), 102.

[18] McDaid, A., Greene, D. & Hurley, N. (2011) Normalized Mutual Information to evaluate overlapping community finding algorithms. *arXiv preprint arXiv:1110.2515*.

[19] Mislove, A., Viswanath, B., Gummadi, K. & Druschel, P. (2010) You are who you know: inferring user profiles in online social networks. In *Proceedings of the third ACM international conference on Web search and data mining*, pages 251–260. ACM.

[20] Moreno, J. (1934) *Who shall survive? : a new approach to the problem of human interrelations*. Nervous and Mental Disease Publishing Co.

[21] Newman, M. (2006) Modularity and community structure in networks. *Proceedings of the National Academy of Sciences*, **103**(23), 8577–8582.

[22] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M. & Duchesnay, E. (2011) Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, **12**, 2825–2830.

[23] Rosvall, M. & Bergstrom, C. (2011) Multilevel compression of random walks on networks reveals hierarchical organization in large integrated systems. *PloS one*, **6**(4), e18209.

[24] Sampson, S. (1968) *A novitiate in a period of change: An experimental and case study of social relationships*. PhD thesis, Cornell University.

[25] Schaub, M., Delvenne, J., Yaliraki, S. & Barahona, M. (2012) Markov dynamics as a zooming lens for multiscale community detection: non clique-like communities and the field-of-view limit. *PloS one*, **7**(2), e32210.

[26] Stabler, M., Lee, C., Williamson, G. & Cunningham, P. (2011) Using Hierarchical Community Structure to Improve Community-Based Message Routing. In *ICWSM 2011 Workshop on Social Mobile Web Workshop, SMW*.

[27] Traud, A., Mucha, P. & Porter, M. (2011) Social structure of Facebook networks. *Physica A: Statistical Mechanics and its Applications*.

[28] Traud, A. L., Mucha, P. J. & Porter, M. A. (2012) Social structure of Facebook networks. *Physica A: Statistical Mechanics and its Applications*, **391**(16), 4165–4180.

[29] Yang, J. & Leskovec, J. (2012a) Defining and evaluating network communities based on ground-truth. In *Proceedings of the ACM SIGKDD Workshop on Mining Data Semantics*, page 3. ACM.
[30] Yang, J. & Leskovec, J. (2012b) Structure and Overlaps of Communities in Networks. In Proceedings of the 6th SNA-KDD Workshop.

[31] Zachary, W. W. (1977) An Information Flow Model for Conflict and Fission in Small Groups. Journal of Anthropological Research, 33(4), pp. 452–473.