Gelly-Scheduling: Distributed Graph Processing for Network Service Placement

Miguel E. Coimbra, Alexandre P. Francisco, and Luís Veiga

INESC-ID Lisboa / Instituto Superior Técnico, University of Lisbon, Portugal
miguel.e.coimbra@tecnico.ulisboa.pt
{aplfr, luis.veiga}@inesc-id.pt

Abstract. Community network micro-clouds (CNMCs) have seen an increase in the last fifteen years. Their members contact nodes which operate Internet proxies, web servers, user file storage and video streaming services, to name a few. Detecting communities of nodes with properties (such as co-location) and assessing node eligibility for service placement is thus a key-factor in optimizing the experience of users. We present an approach for community finding using a label propagation graph algorithm to address the multi-objective challenge of optimizing service placement in CNMCs. Herein we: i) highlight the applicability of leader election heuristics which are important for service placement in community networks and scheduler-dependent scenarios; ii) present a novel decentralized solution designed as a scalable alternative for the problem of service placement, which has mostly seen computational approaches based on centralization.

Keywords: leader election; community detection; service placement

1 Introduction

Nodes in guifi.net are exclusive to specific geographical zones (there are no overlays), such as what is depicted in Fig. 1. There are instances of special-purpose nodes called graph-servers, which are responsible for performing network measurements between nodes [13]. These graph-servers in fact comprise a hierarchical monitoring system which is distributed and records link data traffic metrics.

The properties of guifi.net are such that it is a suitable testbed for developing and validating techniques to enhance service placement and system scheduling by exploring their requirement of leader election. In turn, these may be extrapolated to more complex scenarios, such as placement in P2P networks (typically irregular) and industrial contexts. Our objective was to devise an efficient, scalable solution which is easy to fine-tune regarding domain-specific attributes. This work is a two-phased approach to the challenge of optimizing the definition of communities (addressed in Phase One of our approach) and community leaders (Phase Two) in a communications network. Different services have different needs. Individuals may wish to host functionalities such as proxy variants. For example, a simple web proxy would most likely have node latency as its most relevant parameter. On the other hand, a mission-critical quality-of-service proxy
could place the focus on node availability. Heuristics may encompass network features such as topology, as well as domain attributes (such as availability and quality of resources). While one may intuitively define one heuristic as absolute, this could produce scenarios which are locally optimal but globally undesirable. What if the node with the highest availability happens to be on the outer rims of the network? Clearly the aspects of network topology are as relevant as service-level heuristics which traditionally guide leader election for placements.

The following section 2 explains the two main phases of our algorithm. Section 3 details our evaluation methodology and obtained results. Afterward, in Sec. 4 we highlight other competitive state-of-the-art frameworks which we considered for implementing our algorithm, as well as relevant studies on guifi.net. This document concludes with a summary of our contribution’s highlights and an enumeration of future vectors of research extending from this work.

![Depiction of guifi.net’s Osona region.](image)

Fig. 1. Depiction of guifi.net’s Osona region.

### 2 Algorithm

The first phase is a choice of the targeted definition of community. We used two: default – the zone-based node distributions, provided in the dataset as-is (insignificant pre-processing is performed); scoreless – label propagation as proposed in [12]. We build an undirected graph $G$ by defining a set of edges $E$ such that an edge $e \in E$ will be created if and only if there is a corresponding link element between two working devices (each belonging to a working node) in the dataset. Single-leaf nodes were discarded as part of this preprocessing step. We reiterate that our work focused exclusively on working (this term is clarified later in this document) nodes, in order to maximize the real-world relevance of this dataset.
Community Detection: Next, we provide pseudo-code for the most relevant actions of Phase One, where $N$ is the number of produced communities and $L$ is an upper bound on the number of iterations to execute:

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**Phase 1: Community Detection**

**INPUT:** Graph $G = (V,E)$, Positive Integer $L = 10$

**OUTPUT:** Graphs $\{G_1 = (V_1,E_1), G_2 = (V_2,E_2), \ldots, G_N = (V_N,E_N)\}$ such that $V = V_1 \cup V_2 \cup \ldots \cup V_N$ and $V_i \cap V_j = \emptyset, i \neq j$

1: for each node $v \in V$
2: $v$.generateUniqueLabel();
3: $G' = (V, E')$ ← $G$.setUndirectedEdges();
4: while($G'$.labelsChanged() && $G'$.getIterationCount() < $L$):
5: for each node $v \in V$
6: $M$ ← $v$.getInboundMessages();
7: $v$.updateLabel($M$.getMostFrequentLabels().filterHighestLabel());
8: $L$ ← $L + 1$;
9: return $G'$.groupByLabels();

It is relevant to retain that Phase One is to be executed only in the case of using the scoreless label propagation [12] (for the choice of geographical zones, only the first three steps of phase one would be performed). Phase One thus becomes an important instrument in efficiently defining groups of network nodes. These groups aid the optimization process of service placement, effectively serving as a useful blueprint for Phase Two of our algorithm. Together, the two phases form a technique to harness current platforms and infrastructures to tackle service placement, with the benefits of concurrent job execution and degrees of parallelism within each job.

Phase Two receives a set of communities and elects a leader for each one. This election phase is self-contained for each community, in the sense that a distributed implementation of this phase could be carried out concurrently with respect to communities and in parallel within each community with our graph-based approach.

Calculating the score value for each node $i$ lies in defining a linear combination of two sets of heuristics. One set is based on system-centric values: availability $\beta_1$ and latency $\beta_2$ as defined by graph-servers [2], as well as computational class $\beta_3$ as per Table [2] the other is calculated as part of this algorithm and consists of betweenness $\alpha_1$ and closeness $\alpha_2$ centralities as well as the local clustering coefficient $\alpha_3$. Thus, as an example, the initial score of a node $i$ will be defined as:

$$s_i = w_1 \alpha_1 + w_2 \alpha_2 + w_3 \alpha_3 + w_4 \beta_1 + w_5 \beta_2 + w_6 \beta_3$$  \hspace{1cm} (1)$$

We normalize each heuristic in itself beforehand. This has the purpose of making the heuristics equally relevant for evaluating hypotheses based on geometric or arithmetic means or other weight configurations $w_i \in W, i \in \{1, \ldots, 6\}$. 

**Leader Election:** There may be more than one connected component in geographical zones of guifi.net. Due to this, for every community network \( G \), only the nodes belonging to the largest connected component of \( G \) are used to perform leader election. This election consists of Phase Two of our algorithm:

**Phase 2: Leader Election**

**INPUT:** Graph \( G = (V, E) \), Weight array \( W = [w_1, w_2, w_3, w_4, w_5, w_6] \)

**OUTPUT:** Ranking \( R \)

1. array \([\alpha_1, \alpha_2, \alpha_3]_{v \in V} A \leftarrow G.\text{calculateNodeCentralities}()\)
2. for each node \( v \in V \):
   3. array \([\beta_1, \beta_2, \beta_3] \leftarrow v.\text{getNetworkProperties}();\)
   4. \( v.\text{setScore}(w_4\beta_1 + w_5\beta_2 + w_6\beta_3);\)
3. \( G.\text{sumScoresByVertexIndex}(A * \text{array} [w_1, w_2, w_3]);\)
4. \( R \leftarrow G.\text{getVertices}().\text{orderedByScore}();\)

| Table 1 | Algorithm’s heuristic symbols and meanings. |
|---------|----------------------------------|
| \( \alpha_1 \) | Betweenness Centrality [4] \( \sum_{x,y} 1_{x,y} \), number of shortest paths passing through the node. |
| \( \alpha_2 \) | Closeness Centrality [11] \( \frac{1}{n} \sum_y d_y \), geodesic distance from the node to all others. |
| \( \alpha_3 \) | Local Clustering Coefficient [5] Fraction of connected node neighbors. |
| \( \beta_1 \) | Availability Percentage of ping responses received by a graph-server (%) over a specific time period. |
| \( \beta_2 \) | Latency Ping response timing, measured by a graph-server (ms) over a specific time period. |
| \( \beta_3 \) | Computational Class Defined by the number of devices handled by the node, as well as its role. |

**Heuristics for Node Scoring:** Our algorithm was designed under two types of evaluation based on configuration of heuristics:

- **Absolute heuristics:** leader selection is guided exclusively by exactly one of the heuristics. We analyze the impact of each individual heuristic, setting the weights of others to zero.
- **Combined heuristics:** as a follow-up, we consider a linear combination of two heuristics. We set unbalanced weights in order to better determine the more significant contributions, in the sense that for two heuristics \( m_1 \) and \( m_2 \), we may define the node score to be \( v_s = (1 - f)m_1 + fm_2 \), or
the reverse. If one heuristics weights in for 60% of the score, the other will account for the remaining 40%.

Implementation Details: The two phases of the algorithm were implemented in Apache Flink’s Gelly and DataSet APIs. Scores or heuristics $\alpha_1$ and $\alpha_2$ are obtained for each community $G_i$ using the Python NetworkX library for network analysis at the beginning of Phase Two. Overall, the time to calculate them is negligible when compared to the time of Phase One and two (either summed or individually).

3 Evaluation

Our analysis was based on a snapshot (3rd of January, 2017) of the full dataset of guifi.net, manipulated as described in [3]. The XML-based Community Network Markup Language (CNML) defines an enumeration of possible network node states. There are 23,391 nodes identified as working and, for the whole guifi.net, there are 878 nodes defined as servers. This implies that, at most, 3.75% of the working nodes could actually be sustaining full fledged services. Figure 2 shows, for these server-type nodes in the complete network, the top-five most present services offered. We believe guifi.net, while it is in fact an open commu-

Fig. 2. Top-five most frequent service server types in guifi.net.

1 Access date Jan 10th, 17': https://wiki.confine-project.eu/guifinetcnml:start
analyzed the impact of prioritizing different heuristics on the resources available for operating different types of services on a community network [14]. For evaluation purposes, we defined heuristic $\beta_3$ as a score in three computational categories for nodes: i) server-type nodes which typically have stronger computational power to support services such as those of Fig. 2; ii) non-server nodes with more than one device; iii) non-server nodes with a single device. Table 2 shows the representation of each category for the data we analyzed. This categorization serves the purpose of approximating realistic tiers of computational capabilities for nodes in the network – information which, as far as the authors know, is not readily-available in the guifi.net CNML dataset.

| Nodes | i) Strong | ii) Medium | iii) Weak |
|-------|-----------|------------|-----------|
| 23,468(100%) | 337(1.436%) | 1,666(7.099%) | 21,465(91.465%) |

Table 2. Frequency of per-node device count categories. The most frequent services are Internet proxies, which makes sense as guifi.net exists as an alternative to the standard ISP model.

Experiments were performed on an SMP with 256 GB RAM and 8 Intel(R) Xeon(R) CPU E7- 4830 @ 2.13GHz with eight cores each. To simulate a real-world normal user’s cloud-rented (e.g., AWS) machine, running Apache Flink application instances were constrained to use only a parallelism of one and at most 2 GB of working memory. This was intended to further solidify the realism of our experiments – except for power users, these specs represent a pessimistic assumption on the capabilities of the average user’s computational hardware. Based on results in [1] (Empirical Cumulative Distribution Function of node availability), experiments were performed with availability generated under distribution $\beta_1 \sim \mathcal{N}(\mu = 0.8, \sigma = 0.2)$ and latency under (heterogeneity in guifi.net is such that urban areas have typically lower latencies and rural ones have increased latencies) distribution $\beta_2 \sim \mathcal{N}(\mu = 200, \sigma = 200)$ in milliseconds.

3.1 Network Impact

We present in Fig. 3 the distribution of maximum and average degree versus the size of the communities. The left side pertains guifi.net zone-based communities (from the dataset as-is), while the right side is related to the configuration of network node groups obtained with Phase One of the algorithm. We derive from this that our algorithm produces groupings with a tendency for greater node inter-connectivity. Moving on, we further evaluate this derivation by producing a

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2 Fine-grained technical specifications such as processing power, available main memory and secondary storage would allow for a richer analysis.

3 We have found many public graph-server nodes in guifi.net to not be operational despite being listed as active. This was a source of entropy in the time invested to attempt to get a complete vision of system node metrics.
visualization of the average number of hops-to-leader for each community versus community size. Figure 4 presents this with respect to natural geographical zones of guifi.net in the left, with our algorithm's results in the right. Our algorithm led to an overall reduction in the number of hops, in particular for smaller and more frequent communities. Focusing on Fig. 5, we highlight interesting tendencies with regard to the impact of absolute heuristic weights and their impact on average number of hops. In particular, we achieve this by isolating the range of community sizes to a maximum size of 250 members. Plotting these ranges over a logarithmic scale, it can be seen that the contained communities exhibit a lower number of hops. This tendency is particularly manifested with heuristic $\alpha_1$ and $\beta_3$ (betweenness centrality and computational class of the node, respectively).

We extrapolate from this finding that the fixed-region geographical definition of guifi.net may be too rigid and that it may in fact provide a user experience which is probably below-optimal regarding typical services offered in CNMCs. Techniques based on label propagation show promise with respect to optimizing the length of the path taken from each community's node to the community leader, which is a sure benefit for many services, as those presented in Fig. 2.

3.2 Leader Election Results

Moving on, to get a better grasp on the understanding of the impact of heuristics, we present in Fig. 6 the average values and deviations for the same heuristic weights present in Fig. 5. It is relevant to note that after Phase Two of our algorithm, the application of heuristics over the propagation-based node sets (right side) yielded more outliers than the geographical zones (left side). While there were more outliers in the results of Phase One of our algorithm, they lower values were achieved when compared to the geographical node groups. Lastly, we
Fig. 4. Average number of hops-to-leader plotted against each community’s size. The left image is the geographical configuration of node sets, while the right side is based on Phase One of our algorithm.

Fig. 5. Average number of hops-to-leader plotted against a logarithmic scale of each community’s size. The left image is the geographical configuration of node sets, while the right side is based on Phase One of our algorithm.
present Fig. 6 which depicts the number of average hops-to-leader in decreasing order. Orthogonally to node group definitions, the tendencies in the influence of the heuristics remain valid, with the same patterns appearing for each of the cases. It is interesting to note that, for the right side (based on Phase One of our algorithm), heuristics $\alpha_2$ and $\beta_3$ produced greater differences between them. Accounting for the computational class of nodes in the case of the right side led to a lower number of hops-to-leader compared to simply electing leaders based on centrality. We presented obtained results evaluated under different criteria. Our focus is not on producing a one-size-fits-all hierarchy of heuristics: other real-
world scenarios upon which to test our algorithm will have specific objective functions, bound by application needs.

The results are promising as they highlight that our algorithm is a valid alternative to traditional computational approaches to optimizing responsibility assignment to network nodes. Furthermore, the method we present is inherently parallel and distributed, a break from traditionally-centralized often exhaustive optimization-driven solutions, opening possibilities for scalability. Phase Two of our algorithm was designed to be distributed with the purpose of executing concurrently among all communities. This implies that the computational time of this phase has an upper bound associated to the slowest-computing community.

4 Related Work

As far as the authors are aware, this work is the first that attempts to optimize leader election by defining communities using an analysis based purely on network theory and distributed graph processing applied to an existing topology. It is important to retain that related research pertaining our work is multidisciplinary. First, the guifi.net telecommunications network is one upon which different research projects have been executed [3], [15]. It is an open communication network which individuals may freely integrate. Different studies on this open network have drawn several insights: the network is not homogeneous – rural areas have topology properties different from those of metropolitan areas, such as density; the topology observed in rural areas is not scale free (degree distribution does not fit a power law) due to the high number of terminals connected to some nodes; removing terminal nodes (with degree one) from the graphs in rural areas, however, leads to a scale-free core-network as in [15]. On the one hand, it is necessary to be aware of the challenges inherent to service allocation in different types of networks in the context of distributed systems. On the other hand, we highlight the existence of community detection techniques (in network theory) as a novel approach to these challenges. System scheduling and service placement have many purposes and their underlying challenges are a function of computational infrastructure and service requirements [2], as well as topological properties.

There are many perspectives to interpreting the communities in a network. In recent years, metrics proposals for evaluating the quality of calculated communities have emerged: the most notorious one being that of modularity [9], [10]. However, focusing exclusively on modularity incurs community resolution penalties manifested on two extreme cases. On one side of the spectrum, every single node in the network could be in its own self-contained community (and many agglomerative algorithms for community detection do in fact define this to be the starting scenario of the network). On the other extremity, a single community could be defined: one which contains all nodes in the network (assuming no node is isolated). Considering this, other methods which do not use domain-specific heuristics were devised, such as the class of label propagation
algorithms [6], [12], which is inherently parallel.

We considered other (open-source) systems such as **Apache Giraph** and **X-Stream**. **Apache Giraph** is an implementation of Google Pregel [7], tailor-made for graph algorithms. It was created as an efficient and scalable fault-tolerant implementation on clusters with thousands of commodity hardware, hiding implementation details underneath abstractions. It was inspired by the Bulk Synchronous Parallel (BSP) model. **X-Stream** [13] introduced the concept of edge-centric graph processing via streaming partitions. Most of its introductory cases were based on a single-machine shared-memory setup. However, work has been done to test the feasibility of extending its concepts to take advantage of network-based computing resources [8]. **X-Stream** exposes the scatter-gather programming model and was motivated by the lack of access locality when traversing edges, which makes it difficult to obtain good performance.

In the end, it was decided to leverage the graph processing framework **Apache Flink**. We opted for **Flink** due to its rapidly-growing community and rich graph API **Gelly**. It has a graph processing API called **Gelly**, which packages algorithms such as PageRank, Single-Source Shortest Paths and Community Detection, among others. Researchers are currently looking into extending its **DataStream** constructs and its streaming engine to deal with applications where the incoming flow of data is graph-based.

5 Conclusion

In this paper, we presented a novel take on the processing steps that underlie service placement, a multi-objective problem. Compared to traditional system techniques (which, as far as we know, have not seen developments regarding parallel implementations and scalability with network size), our algorithm is expressed purely over state-of-the-art graph techniques which have inherent parallelism. This makes our algorithm a very competitive alternative which should be able to scale for networks which are orders of magnitude greater, when compared to other traditional techniques in the field. Our algorithm is thus a simple and intuitive method designed to benefit from the knowledge on the type of service or domain of application (in the form of heuristic coefficient adaptation).

As for the future, we see value in pursuing applications of this work for optimizing the analysis and service placement for irregular infrastructures such as P2P networks, as well studying its applicability in data centers. In that context, when dealing with incoming streams of information (on systems such as clouds), the ability to keep communities updated becomes a crucial operation for the efficiency of schedulers. It would be important to extend the parametrization of our work to account for leader election with more than one leader per community – with a reduced number of leaders to be met, it is imperative to nominate the best possible candidates (another domain where this problem appears is in sensor networks).
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