Literature Review Project Report Template

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1. Introduction

Many systems may be described as networks.In these networks, the nodes can be considered as individuals as well as web pages, and edges are the connections among them.

The Louvain algorithm is one of the most popular ways to find communities. It starts by looking for the best modularity score, even on huge graphs, it is so fast because of its simple steps.So it has become a standard tool in network science and used in many fields.

Researchers have found some problems, like the resolution limit,scale of a graph and the fact that results can sometimes change easily. Because of these issues, many studies have suggested updated versions to the original algorithm.

The goal of our review is to organize the research and the developments have been made to Louvain based community detection. By reading and analyzing 80 research papers, we want to understand how the Louvain algorithm has been improved over the last years, where it works well or bad, and how it is compared to other methods of finding communities.

2. Research Focus and Core Questions

This literature review is centered on research involving the Louvain algorithm for community detection in networks. Our approach is not a simple enumeration of individual studies; instead, we aim to synthesize how the Louvain method has been applied, refined, and evaluated across various contexts.

The review is structured around the following primary research questions (RQs):

- **RQ1 – Scalability and Performance:** The Louvain algorithm and its variants are prominent optimization heuristics in network community detection, known for their successful deployment and efficiency.
- **RQ2 – Community Quality and Resolution Issues:** To address recognized limitations, such as the modularity resolution limit or partition instability, methods have been proposed to enhance the quality of the communities detected by

Louvain.
- **RQ3 – Comparisons and Applications:**
- The examination of networks, including geographical networks like US transport networks and social media networks like Twitter and Facebook, can benefit from using multiple community detection algorithms for effective topology analysis.
- To obtain detailed insights, we may also consider the following sub-questions. What types of networks (social, tech., etc.) mostly appear in the development and testing process of Louvain? What metrics are generally evaluated (i.e modularity; time; RAM)?
- Which are the Louvain variants or similar algorithms that present evident advantages vis-à-vis the original algorithm, and under what specific conditions do such advantages emerge?

These questions establish the scope of our review and guide the thematic organization of findings from the selected literature.

3. Literature Review Methodology

This section outlines the systematic procedure used for identifying, selecting, and screening the articles that form the basis of this review. Our goal is to detail the process that resulted in the final corpus of 80 research papers.

3.1 Search Strategy

Two primary databases were utilized for the search:

- **Google Scholar**
- **IEEE Xplore Digital Library**

Initial attempts using broad keywords like "Louvain" or "community detection" alone were either too non-specific or resulted in irrelevant articles (e.g., "Louvain" not referencing graphs, or "community detection" focusing on non-Louvain algorithms). Effective, targeted results were achieved by combining the concepts.

The consistent search phrase employed for systematic database queries was:**"Community detection using the Louvain algorithm"**

Since this approach tended to result in a comprehensive set of final, highly-cited papers that were linked through Google Scholar to publisher sites such as Springer Nature, ScienceDirect, Wiley Online Library, and IEEE, we found this approach to be sufficient. The search was constrained to English language papers, starting from 2008-the publication year of the original Louvain method-to the present date in order to capture all relevant work.

3.2 Selection and Filtering Criteria

The initial search questions yielded around 100 research papers. This was followed by the screening process based on the title, abstract, and the full text when needed.

Inclusion Criteria:

- Review included journal and conference papers that are peer-reviewed. Because of the algorithm's relatively extensive coverage, we also include workshop papers that are perceived to be of good quality. The report must be written in the English language.
- Any paper that uses, focuses on confirming or analyzing the Louvain algorithm (and variants), or the graph.

- The article should help answer at least one of our questions, including algorithmic advances, performance evaluation, quality assessments, or applications.

Exclusion Criteria:

- The term "Louvain" does **not refer to the algorithm** (e.g., a place name or institution).
- The term "community" is used in a **general or sociological sense** and not in the context of community detection in graphs.

- The Louvain method is only mentioned in **passing** without meaningful analysis, results, or discussion.

Applying these criteria led to the discarding of about 20 irrelevant papers. Ultimately, a final corpus of **eighty papers** directly focused on Louvain-based community detection was established.

3.3 Final Corpus and Organization

The papers were accurately documented in a communal excel form. In addition to the standard details provided by the papers themselves (such as authors, the year of writing, and where it was presented), the following details were considered crucial:

- **Contribution Type**: Original Louvain, variant/improvement, application, or theoretical analysis/case study,
- **Network Types Considered:** Undirected, weighted, directed, temporal, or multilayer networks.
- **Primary Focus Area:** Scalability/performance, quality/resolution, comparison, or application.

This structured data allows for categorization according to our main research questions (e.g., papers focusing on scalability-driven variants vs. those addressing quality or resolution limits). This thematic grouping provides the foundation for the synthesis in Section 4 and the comparative analysis in Section 5.

4. Summary of Key Literature Themes

This report offers a summary of the key findings gathered from the 80 papers in the corpus, progressing from the level of individual studies to broader themes. All the papers in the corpus were annotated for characteristics including the type of contribution, the main topic of each contribution (Scalability, Quality, Comparison, Application), the type of networks, and the corresponding metrics used.. When grouped by these tags, the corpus naturally clusters into four central themes:

1. **Scalable and parallel variants of Louvain** designed for processing large static

graphs.

2. **Methods that enhance community quality**, address resolution limits, or support overlapping and fuzzy communities.
3. **Dynamic and temporal extensions** of Louvain for use with evolving networks.
4. **Domain-specific applications** where the Louvain method is integrated into larger data analytics pipelines.

Furthermore, a significant portion of the literature serves as comparative or methodological references, contextualizing Louvain against competing algorithms or examining its robustness and evaluation practices. The following sub-sections will describe each theme by detailing the specific problems addressed, the proposed techniques, the common datasets and metrics employed, and the main emerging patterns in the research.

4.1 Scalable and parallel Louvain variants for large static graphs

A large part of the literature is devoted to optimizing the Louvain method to handle large networks efficiently. According to the tags and categories related to scalability (for instance, "speed/scalability" or “parallel community detection”), it appears that a large number of documents can be identified as primarily “performance-oriented” variants of the method. These research initiatives share the starting point that, as efficient as it is, the original Louvain method is simply not designed for graphs of “a few million nodes and edges” or “graphs that are frequently updated” and therefore exceeds the method’s capabilities in those cases. The two most prominent targets in this category are runtime and memory.

Within these, some set of research papers optimizes the Louvain algorithm by accelerating it through the local move phase or supplementing the method with structural heuristics. Some of these research papers propose the use of cliques or dense subgraphs to control the movements of nodes, which results in faster execution. Others propose the use of edge centrality measures or new schemes for node ordering, which improves the efficiency of modularity optimization. A general theme in these research papers appears to be the observation that the modularity value computed remains comparable to that of the original Louvain algorithm, although the execution time can be reduced by significant margins for Facebook ego, citation, and co-authorship networks. The metrics reported by these research papers consistently include:

-Modularity

-Execution time

-Number of communities or speedup compared to a sequential solution

Another category revolves around parallel and distributed execution. Examples here include shared memory parallel Louvain on multi-core CPUs, parallel Louvain on GPUs, and distributed memory algorithms for clusters and big data infrastructures. Categories here use terms such as 'Parallel Community Detection', 'GPU-based parallel Louvain', or 'Distributed Louvain'. These take advantage of the local move parallelism aspect by carrying out multiple nodes simultaneously, breaking up the graph into independent parts, or reducing the strict ordering of the original algorithm. On large real-world graphs, such as web graphs or large-scale social media sites, the speed-up graphs are often linear, assuming a large enough graph. Metrics measured for the evaluation of these papers include running times, speed-up values, and, occasionally, memory use, with the use of modularity connecting to ensure that community structures are not degraded by parallel processing.

The third type of work that is network-related is incremental and/or streaming-style improvements, and is most apparent in works where the category advertises “incremental”, “fast dynamic”, and/or “efficient updates”. Even for a network that does not actually change, edge additions and removals over time can make full updates expensive. The incremental versions of Louvain reuse the former partition to start with and locally update communities in response to graph modifications without actually having to compute everything from scratch each time. Within the corpus and on the temporal and incremental datasets that represent evolving social, email, and/or finance graphs, these algorithms generally provide a good trade-off in that they come very close to the modularity values attainable in a full Louvain run but with a strongly reduced runtime cost for each update. The literature on scalability generally agrees that while Louvain's multi-level greedy approach is highly susceptible to parallelization, heuristics, and incremental updates, good speeding up advances can be found that do not impair the algorithm's position as a good proximity measure benchmark.

4.2 Community quality, resolution, and overlapping or fuzzy extensions

A second overarching theme in the dataset concerns the enhancement of community quality, in the sense of breaking the resolution limit of the modularity resolution problem or more generally the detection of overlapping communities. Tags related to quality appear in the great majority of papers, and there is an especially focused collection of papers in which the related category title and content specifically use “resolution limit”, “quality improvement”, or overlap detection. These papers address well-known shortcomings of maximum modularity, which amalgamates small communities in large graphs and the traditional Louvain method, which yields exactly one sharp partition to which each node is assigned to exactly one community regardless of the fact that nodes in many real-world systems belong to multiple communities.

A number of papers directly deal with the problem of the resolution limit using techniques that modify the objective function. There are edge-weighting and diffusion-based preprocessing techniques proposed to adjust the effective resolution of modularity functions. In this approach, instead of using the original modularity function as an objective function to be maximized, they first use edge reweighting based on local topology and/or diffusion, in which case smaller communities receive increased importance. Their experiments using synthetic datasets such as LFR networks and real-world social networks indicate that these techniques are able to detect smaller ground truth communities than Louvain as measured by:

-Modularity at various scales/advantages.

-Normalized Mutual Information (NMI)

-Adjusted Rand Index (ARI)

Some other works focusing on quality involve multi-objective optimization, incorporating the idea of modularity and other tasks like structural similarity, consistency, or community compactness, resolved by tools involving evolutionary or heuristic optimization techniques. In these studies, the listed performance metrics are modularity, as well as other task-specific metrics like AUC, precision, recall, and accuracy.

Another set of papers related to this theme is dedicated to overlapping or fuzzy community detection. These papers cover node-centered extensions of Louvain enabling a node to belong to multiple communities according to its incident edges, overlapping communities via cliques, as well as fuzzy models designing memberships as degrees. The category tags of these papers include phrases like “overlapping community detection/Louvain-based heuristic,” “fuzzy & overlapping community detection,” or “new overlapping Louvain variant,” while the tags include codes related to overlapping. In these papers, research analysis is conducted using overlapping versions of NMI/Omega index and modularity-type metrics adjusted for overlaps. In general, these studies conclude that Louvain heuristics can be applied in overlapping communities efficiently, while these communities effectively identify multi-role roles of nodes in social, collaborative, or document information networks, as opposed to hard partitions.

Finally, there are studies that specifically examine the stability and robustness of quality assessment and the resulting partitions themselves. For instance, there is one study in the literature that investigates the instability of the quality of clusterings in the context of community structures with overlaps and finds that even small changes in the partitions can cause substantial differences in the quality of the assignments. There are also studies that investigate the influence of varying the random seed or the order of nodes or small perturbations of the network on the results of the modularity function using the Louvain method. All of these studies illustrate the high degree of degeneracy of modularity and that there can be rather distinct partitions that have rather close modularity values. Therefore, there is a trend in the literature towards the application of techniques that can produce rather stable assignments using ensemble methods or consensus cluster analysis or running the program multiple times. Overall, this literature with the primary focus on quality indicates that although the modularity function and the resulting modularity optimization in the Louvain method can produce rather fast and simple results with minimal computational costs and efforts, it is rather difficult to produce rather high-quality results using this method or technique.

4.3 Dynamic and temporal Louvain variants for evolving networks

A third category comprises dynamic, temporal, and evolving networks for which the community patterns are also dynamic and change over time. The dynamic-related keywords and their respective categories, such as “dynamic community detection,” “temporal modularity,” and “incremental community detection,” are found in emerging portions of the corpus. These papers contend that simply applying the static Louvain method repeatedly for every time point is ineffective for taking advantage of the temporal smoothness and can be computationally expensive, especially when it is done for every time point or when the communities change slowly.

There is one line of research which has considered dynamic variants of the algorithms which take into account the adaptation of the Louvain algorithm on dynamic graphs. These methods include approaches which keep the hierarchical layout of the initial communities as determined in the initial run of the Louvain algorithm. While these methods update the layout locally with the addition or removal of edges in the graph, they do not require a recalculation of the entire graph. They instead recalculate the layout of the locally affected nodes in the graph. The experiments performed in these research studies include evaluation of the modularity of the algorithms. The measurements taken in these studies include:

Occasionally NMI between community graphs from different snapshots to capture community smoothness change.

The next group of research papers employs a modularity framework with multiple layers or a temporal perspective, where every snapshot in time represents a layer and connections between layers indicate node similarities across layers. The Generalized Louvain algorithms are applied to maximize a multi-layer modularity objective, aiming for a balance between layer modularity and multi-layer alignment. Research papers with dynamic keywords like temporal and/or multi-layer and/or temporal networks belong to this category. The techniques are applied to temporal benchmarks and real citation networks and/or social processes, leading to smoother communities in temporal networks with reduced noise sensitivity at the expense of introducing new parameters to control layer connections.

Other dynamic approaches based on different ideas from models mentioned above also exist, like game-theoretic formulations where nodes optimize their community assignment to maximize the neighborhood reward, and adaptations of algorithms like Label Propagation Algorithm to dynamic graphs. Some papers compare the different approaches to dynamic Louvain methods based on measures like modularity, NMI, ARI, and running time. The dynamic literature also indicates that it is possible to successfully modify the basic greedy approach of the Louvain method to handle dynamic networks by incremental or multilayer techniques.

4.4 Domain-specific applications and Louvain in larger analytical pipelines

The fourth theme that emerges from the corpus regards domain applications where the employment of the Louvain algorithm is a part of a larger investigation or prediction pipeline. Based on the tags that belong to the application domain, it seems that a large number of papers belong to this category. This category of papers tends to contribute more to understanding the application possibilities of Louvain as a feature provider rather than advancing the method as such.

Energy and infrastructural networks represent another significant application area. There are several studies that use the Louvain algorithm or its variants to study the structure of power networks, smart power networks, and water supply infrastructural networks. These studies include investigations of community structure and centrality in the transmission network of electric powers, studies of community structure in water supply infrastructural networks, and investigations employing modified versions of the Louvain algorithm to identify communities for smart grid datasets based on the clustering of the load profiles of the nodes. In these studies, instead of assessing the quality of community structure, the community structure interpretation in terms of, for instance, functional zones of the power network, and its applicability for instance, for risk analysis, and for planning purposes, take primary importance.

The second family of application papers is related to recommendation systems, graphs of user-item interactions, and online platforms. Within these papers, the Louvain method is applied to uncover communities of users or items. These communities become a part of hybrid recommendation models or serve as hidden groups for collaborative recommendation. The typical example of such applications appears in articles that summarize a recommendation method that applies both the singular value decomposition technique and community discovery with the Louvain method or integrate the Louvain method into multistage recommendation models. The evaluation often goes past the community structure. Instead, it is based on recommendation precision, the root-mean-square error (RMSE), precision, recall, or click-through rate. The takeaway is that community-aware recommendation models utilizing community structure uncovered with the Louvain method lead to better predictions than models that ignore community structure.

Another group of application domains is security, finance, and cyber-physical systems. Some articles introduce the application of the community detection method based on the Louvain algorithm within blockchain botnet detection, credit risk, or fraud evaluation, network security risk modeling, and speaker diarization tasks. In these cases, communities refer to groups of suspicious addresses, dangerous consumers, attack behavior, or speech activity, respectively. In general, articles include the evaluation of the result of the community detection method in metrics such as AUC, detection rate, or diarization error rate, not limited to modularity. These examples provide clues about how communities generated by the Louvain algorithm can be treated as high-level structural features to enhance the performance and interpretability of complex detection systems.

Finally, there are research works that combine Louvain with contemporary graph learning methodologies like graph neural networks and attention models for clustering. Some of these studies examine learning-based models for communities by comparing them with Louvain on benchmark examples, while other works develop learning-based models for community detection, incorporating Louvain perhaps for initialization. The respective categories contain phrases like “Learning-Based Community Detection and Comparison with Louvain” and “Neural and Interpretable Community Detection for Directed Weighted Graphs.” Overall, these research pieces confirm that, even with the development of new models for trendy fields like deep learning, Louvain is continuing to be a standard referent and baseline.

Summary:

The application literature clearly indicates that Louvain-based methods for community detection find practical use in a vast array of applications, entering areas like infrastructure, security, and recursive systems and software development, and that this can be expected to remain a trend with new models being developed to fulfill contemporary demands.

5. Comparative Analysis and Discussion

This section will compare the major themes in the literature with the research questions formulated in section 2. Instead of presenting further collections of articles, this discussion will contrast the four thematic clusters of section 4 according to various criteria:scalability and performance (RQ1), community quality and resolution problems (RQ2), as well as comparisons and applications of the Louvain algorithm in real and model networks (RQ3).OURNALAdditionally, aspects of stability and robustness, the position of the Louvain algorithm within the context of more modern approaches, as well as a brief description of a computational experiment on a specific algorithm presented in reviewed articles.

In general, the literature shows that the Louvain method remains an essential benchmark, but hardly ever appears on its own, and usually pertains to modifications, extensions, or integrations into broader systems. The next sections will provide insights into the key findings from the comparisons.

5.1 Scalability and Performance Across Louvain Variants (RQ1)

The literature on performance optimization consistently demonstrates that Louvain-type algorithms exhibit good inherent scalability, and that further efficiency improvements can often be achieved without drastically changing the core algorithm. The specific methods for accomplishing this vary among the three sub-categories discussed in Section 4.1.

One approach involves **heuristic and structural accelerations**, such as using dense substructures, node-ordering heuristics, and edge reweighting based on local topology. These techniques have been tested on medium- to large-scale real-world networks, including social, citation, and collaborative graphs.

In these experiments, the general finding is that...

The modularity gained by the accelerated version is, in general, very close to, or slightly better than, the original version of the Louvain algorithm.

Running time improves significantly with a non-trivial slowdown factor expressed in terms of percentages and ratios of speedup.

Memory use is rarely a concern, though sometimes extra overhead is involved by preprocessing tasks such as clique or centrality computations.

These approaches become most appealing when the network is relatively large and easily fits into memory, or when repeated calls to the same network run are needed (say, when evaluating different choices of parameters or the seed).

Second, parallel and distributed versions of Louvain demonstrate that this algorithm has high affinity to multi-core, GPU, and distributed computing models. In this case, the comparison in terms of scalability focuses on:

-Speedup vs. number of processors or threads

-Maximum network size that can be handled

-Loss (preservation) of modularity with respect to the sequential baseline

The differences between parallel and sequential models tend to be minute in most known experiments, implying that the local greedy property of the Louvain method is robust against a certain level of disregard for ordering. The key trade-offs depend upon both implementation and hardware. When computing power is a problem, models based on either GPU or clusters demonstrate remarkable speedup for large graphs; however, their applicability is limited.

The third set of models combines scalability and dynamics. Though applicable to temporal networks, they are primarily beneficial for computational reasons—their main benefit lies in the reduced repeated costs of reclustering. As compared to computing everything anew, they:

Incremental Louvain algorithms require similar modularity values but have much smaller update times. They depend very much on the quality of the former partition for initialization, and if the network structure varies significantly, their benefit can be reduced. In conclusion, based on RQ1, from the existing literature, it is seen that the Louvain method is actually a strong efficient algorithm itself, but it can be improved significantly by using heuristic, parallel, and incremental strategies. The strategies that work best would depend on whether a parallel strategy for GPUs or an incremental strategy is required based on whether the graph is constantly changing.

5.2 Community quality, resolution, and trade-offs in objective design (RQ2)

Regarding RQ2, the research question that arises for the case of the community quality of Louvarelated methods is: How do the methodologies related to Louvain address the quality of the community, especially the resolution limit and the robustness of the optimal partitions?

The related literature indicates that a wide range of methodologies have emerged, each

Those methods modifying the objective function (such as through the use of edge reweighting, modularity with multiple resolutions, the use of CPM-style Hamiltonians, or multi-objective formulations) are typically found to enhance the detection of smaller or meaningful communities:

With artificial benchmarks where ground truth is known (so called LFR networks), these algorithms tend to provide a higher NMI or ARI index than the basic Louvain algorithm, particularly if ground truth communities are small or of different sizes.

They may give rise to lower raw values of modularity, and an important conceptual point that emerges from this is that higher modularity does not necessarily imply higher alignment accuracy.

Multi-objective approaches can represent more complex patterns (e.g., interacting modularity and attribute similarity), although they also entail more parameters and can be more difficult to interpret.

Extensions dealing with overlapping and fuzzy communities can be considered further in relation to this tradeoff. Overlapping Louvain algorithms:

Use a more accurate representation of the nodes which relate to various function sets in social and collaboration networks.

Using overlapping quality measures such as overlapping NMI, Omega, and so on, making it more difficult to compare to the traditional hard-partition modularity measure directly

To be computationally more expensive because of multiple membership, but various studies have found them to perform acceptably on large but sparse graphs.

Analyses of stability and robustness indicate that the optimization problem of Louvain has an extremely degenerate landscape because there can be similar modularity for different partitions. As a consequence of this situation, there are two possibilities

Sensitivity to random initialisation/ordering of nodes.

Variation between runs, even on the same data set, especially with respect to a weak community structure. To overcome these challenges, consensus clustering and ensemble clustering methods can be used. At the expense of greater computational cost, these methods combine the results of multiple runs to provide more reliable results. From the point of view of a comparative study, the findings indicate that the quality of communities cannot be effectively determined on the basis of modularity, and communities that are meaningful and stable may necessitate more refined functions or ensembles. In summary, literature on RQ2 suggests that while the basic modularity optimization algorithm in Louvain is a good starting point, it is inadequate where resolution and interpretability are important. Modularity extensions that explore multi-resolution concepts, other null models, and overlaps are generally improvements in terms of quality but introduce complexity and lessen the simplicity that made Louvain appealing to begin with.

5.3 Stability, robustness, and dynamic behaviour

The dynamic and robustness-centered literature bridges RQ1 and RQ2 by investigating how stable Louvain-type algorithms are when faced with noise, missing data, or dynamic processes. Across both dynamic and static networks, some patterns emerge.

Studies of static robustness show that Louvain communities are reasonably stable under strong community structures (e.g., dense, isolated clusters), but:

Small increments in sparse or weakly modular graphs might cause a noticeable variation in the final partition.

The external measures can vary even if modularity does not vary much, again emphasizing degeneracy in the modularity landscape.

Dynamic and temporal versions provide a further extension. The incremental and multilayer versions of the Louvain method tend to generate smoother community paths over time compared to the method applied to each dynamic snapshot separately in the same way as for the static case. However, note that a strong temporal coupling can impose stability at the expense of neglecting sudden but significant variations in the structure.

“Weak coupling enhances sensitivity, potentially lifting limitations on detection, but can cause instability”

Overall, the above results indicate that high-quality community detection in a coherent manner in time is still an unsolved task and that Louvain methods, being versatile, should be used with caution when dealing with time-evolving or noisy graphs.

5.4 Role of Louvain in comparisons and applications (RQ3)

- Regarding RQ3, literature assign Louvain mainly two principal roles: one as a baseline for comparative studies and the second one as a building block in application pipelines.
- In comparative evaluations, Louvain is often the modularity, based reference algorithm that is directly compared to the new methods. A paper

proposing a different heuristic, spectral or label propagation method, evolutionary algorithm, or graph neural network based approach will almost always consider Louvain for its experimental comparisons. Typical results are:

- Louvain stays strong in terms of modularity and runtime, especially on large sparse networks.
- Recent methods could be better than Louvain in terms of external quality metrics (e.g., NMI, ARI, F1) for some benchmarks, notably if they are explicitly designed for those datasets.
- In this case, deep learning and GNN, based methods are generally able to achieve better performance on the node classification or link prediction task, although the computational cost is significantly higher and the predictability of the algorithm is lost.
- In the case of applications, Louvain is usually more of a structural than a predictive tool. It is employed to:
- Identify communities or clusters that are used as interpretable units (e.g., regions in power grids, demand groups in smart grids, functional zones in water networks).
- Give features or hidden groups to a model that will be used in recommender systems, security risk analysis, fraud detection, or speaker diarization.
- Act as a pre-processing step or baseline for newer methods, particularly in graph learning pipelines.

More generally, the common pattern seen in various fields is that the communities discovered by the Louvain algorithm are valued for their ease of interpretation and simplicity, although better models are the eventual drivers of the performance in the prediction or classification. This means that although the Louvain algorithm is sometimes beaten in various tasks by different techniques, the algorithm is not usually shelved, as it is always taken as the benchmark.

5.5 Contradictions & gaps and open issues in the literature

In spite of the general coherence of the Louvain ecosystem, it also underlines some contradictions and gaps that are important for interpretation when considering the results found in the survey.

First, there is a tension between modularity and external quality metrics. Some works indeed report very high values of modularity while the NMI or ARI wrt. ground truth or domain labels are relatively modest, in particular in heterogeneous or overlapping settings. That would suggest that modularity can be really misleading and improvement of modularity does not always translate into more meaningful community structures.

Second, practices of evaluation are heterogeneous. Having different benchmarks, metrics, and parameter settings makes comparison across studies difficult. For instance:

-Some works mainly rely on synthetic benchmarks with planted partitions, whereas others focus on real networks without clear ground truth.

-Metrics vary, including modularity, NMI, ARI, F1, and Omega, among others, combined in different ways.

-Therefore, it is also often complicated to claim with great certainty which is the “best” Louvain variant, since performance depends so much on context and many statements result from specific datasets or tasks.

Third, in most cases, robustness and stability have not been systematically evaluated. While a number of papers study sensitivity to perturbations, noise, or temporal changes, a majority of the algorithmic variants are mostly tested on fixed graphs with only a few runs. In fact, given both data uncertainty and evolving conditions in realistic settings, questions can still be raised regarding the behavior of these methods.

Finally, there are the not-so-well-explored problem dimensions, represented by combinations of such as Overlapping, Dynamic, and attributed Networks. Some works handle each of these aspects separately-for instance, overlapping but static, or dynamic but hard-partition-but the research on methods that jointly handle the overlapping, temporal, and attribute-rich community structures within a Louvain-like framework is somewhat limited.

5.6 Representative algorithm and planned computational study

As an add-on to the literature comparison based on the literature analysis performed in the last section, there will be a concrete example using one of the many representative algorithms identified from the surveyed literature. The aim is to check if the observable phenomenon identified in the literature can be replicated using a controlled dataset and the trade-offs identified in this section.

One natural candidate for an example algorithm is a version of the Louvain algorithm, widely cited and well documented, for instance:

A quality-focused variant (e.g. multi-resolution or edge-weighted modularity) that suggests an improvement for the detection of small communities; or

A known improved algorithm like Leiden, which aims at forming well-connected communities, widely known to be faster and more accurate compared to the Louvain algorithm

The proposed computer simulation can be organized in the following way:

Dataset Selection:

One synthetic dataset (e.g. an LFR network with known communities and adjustable size and mixing parameters).

Real-world network (e.g., a social or collaborative network of modest size) where the structural properties are known to be of interest.

Algorithms to compare:

Original Louvain algorithm (baseline).

The chosen representative variant, such as the selected multi-resolution variant or the Leiden variant.

Metrics to measure:

Externally evaluated quality measures between the synthetic benchmark and the ground truth (NMI, ARI, F1).

Runtime and, if possible, memory statistics.

For real-world graphs, modularity and examination of community size distribution or domain-related structure.

Analysis plan:

Comparison of the scores achieved in these experiments can be made with respect to the trends mentioned in the related paper (for instance, better detection of small communities, maximum NMI, and better-connected communities).

Analyze if the empirical behavior that emerges on the chosen data sets agrees with the assertions presented in the literature, as well as how robust the findings are to the values of model parameters (such as the resolution parameters).

Think about how the trade-offs identified from what has been observed (quality versus runtime, resolution versus size of community, stability versus sensitivity) relate to the larger comparative picture that has been established in this section. This small experiment will not substitute the broader literature review but will offer a concrete example of the behavior of a particular algorithm based on the Louvain method in a real-life scenario. It will further illustrate how the lessons of the literature review can be used in a concrete empirical test.

Section 6.Conclusion, Future Work, and Team Contributions.

the main points that surfaced during the literature review, as well as the research gaps. It throws light on the future research streams expected to be adopted in the future. Likewise, it demonstrates whatever are the variations in the work of the team members.

6.1 Conclusion

In this case, the focus will be on studying and examining the existing literature regarding the Louvain algorithm and its modifications for community detection.. Based on an initial corpus of 80 papers, three research questions are taken for the analysis of the Louvain algorithm: RQ1- Scalability and Efficiency of the Louvain Algorithm, RQ2- Community Quality and Resolution Limitations of the Louvain Algorithm, and RQ3- Comparison and Applications of the Louvain Algorithm.

Concerning RQ1, the literature has confirmed that the original Louvain algorithm is indeed a strong and efficient benchmark by which to compare community structure extraction from large graphs based on modularity. Indeed, the community on the R+Q benchmark page claiming to hold the record for the largest community extraction offers the results for the original Louvain algorithm to compare to those of the enhanced version considered in this study. Other studies confirm that the original Louvain algorithm has reached an optimum regarding the structure extraction of communities, and improvements can only come from optimization regarding execution speed and/or efficiency of the algorithms used.

Regarding RQ2, the literature papers under review highlight that in practice, maximization of modularity has several limitations, first and foremost the resolution limit and lack of stability of clustering partitions. These problems can be tackled in many different variants that aim to overcome them by adding to or modifying the objective function (multi-resolution modularity, formulations inspired to CPM, edge weight redefinition, or multi-objective functions), or adding an overlap and fuzzy component to the models. These methods can considerably optimize external summary metrics like NMI and ARI in context of ground truth data, and especially when dealing with smaller communities. However, they also pose further problems and stresses another aspect that was highlighted in this review: that maximum modularity does not automatically imply significant community structure.

To address RQ3, the literature regards Louvain as playing two different but complementary tasks. On one hand, it is a baseline algorithm to compare against, whereby a novel heuristic, quality function, or learning algorithm can be compared against Louvain as a measure of improvement or assessment of algorithm performance. On the other hand, Louvain is a critical module within domain-specific algorithms, such as power & smart grid analysis, water networks, recommendation systems, security & fraud analysis, financial analysis, and speaker diarization systems, to cite a few examples. In these applications, Louvain communities are used as explanatory structures that can be inspected directly or as input to machine learning models, even if other, presumably more complex, algorithms are more effective within a specific task domain. In such cases, Louvain is very seldom replaced by a more effective algorithm but simply supplemented as a valuable tool within the toolbox.

As can be deduced from the analysis above, the Louvain method has developed over the years from a single algorithm to a series of approaches. Each of the approaches weighs different parameters in the aspects of computationally expensive versus resolved solutions or models, and usually the “best” approach is case-sensitive. The proposed computational analysis of the representative approach described in section 5 below is expected to contribute to the demonstration of the above trade-offs.

6.2 Future Work

The literature analysis also shows several areas of open issues, as well as directions of research. These issues pertain both to algorithms as well as applications.

From the algorithmic viewpoint, a research direction of high relevance is the construction of algorithms capable of dealing with several complicated aspects of real networks simultaneously. It is indeed the rule in the community detection area that proposals are made tailored to a specific aspect of networks. While methods addressing two aspects are already quite scarce, approaches considering several complications simultaneously are exceptional. The design of algorithms of the Louvain type able to efficiently process dynamic attributed communities potentially overlapping is a promising research challenge.

Second, there is the area related to practices of evaluation and robustness. It is apparent in the review that the outcome of the performance is closely associated with datasets, metrics, and parameters. Some ways in which future studies could improve involve:

Collections of synthetic and realistic networks with a common ground truth or proxy labels.

Multiple parameters (modularity, NMI/ARI, stability, and performance) compared in standardized fashion.

Analytic treatment of robustness under noise, sampling, and time perturbations.

Practices such as these make it simpler to compare variants of Louvain equivalently, as well as determine within what systems each algorithm is to be used.

A third approach would be to combine the idea of heuristics from the Louvain method and current advancements in learning graphs. Some current studies have already employed the use of the Louvain method. Future studies can focus more on the interaction between community discovery and representation learning, and how it can be used in a different way such that it can initialize or aid in the explanation of representation learning. Of course, it would not be appropriate to neglect the balance between predictive and explanatory abilities.

To conclude, there is the possibility of extending the computational experiment that will be proposed by this project. Instead of only comparing a representative variant with the standard method, the next steps that could be considered might include the comparison of multiple variants (such as a multi-resolution approach and a dynamic model), more varied data sets, or a range of different criteria.

6.3 Team Contributions

Kerim Hariri (Team lead and integration) organized the workflow, merged all sections into one report, and handled final editing. Read and summarized 20 papers.

Mohamad Attia Eid (Literature & citations) managed the literature review content and prepared the IEEE reference list and in-text citations. Read and summarized 20 papers.

Elnur Aliyev (Technical validation figures) checked algorithm accuracy and prepared/updated diagrams and visuals. Read and summarized 20 papers.

Zaid Hardan (Methodology & QA) wrote methodology/comparison parts and reviewed formatting and completeness. Read and summarized 20 papers.

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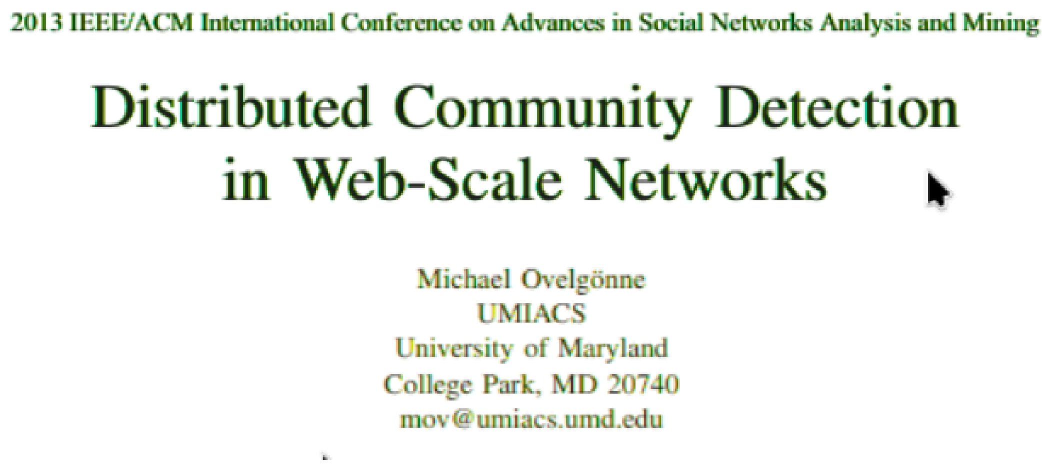
7. Presentation's Case Studies

7.1 Community Detection in Web-Scale Networks for Search and Retrieval



2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining

Distributed Community Detection in Web-Scale Networks

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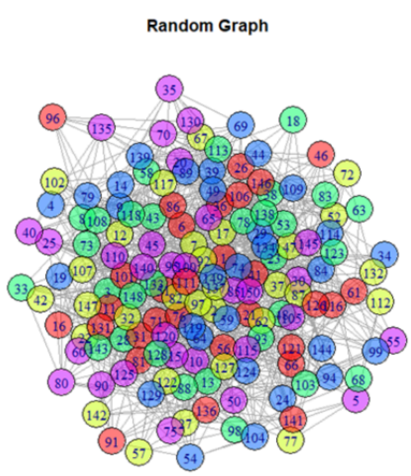
Source: [79]

Community detection is very important for understanding structure in large-scale networks,because it reveals groups of nodes that are strongly connected to each other than to the rest of the graph.

However as the graph size increases as we start using graphs that have millions of edges and vertices ,which are called web-scale sized networks,algorithms start to struggle.

The main challenge is therefore scalability: we need methods that remain efficient and practical even when the graph is too large to process on a single machine.



Source: AI generated Photo

Distributed Community Detection Approach.This paper addresses this scalability issue by proposing a distributed community detection method that uses parallelism across multiple machines. Instead of running the full community detection pipeline sequentially on one computer, the work is split into distributed tasks so that computation and memory requirements are shared.This distributed way of processing makes community detection possible and efficient for very large graphs,which reduces runtime and enables the handling of networks that would otherwise be computationally problematic at web scale.

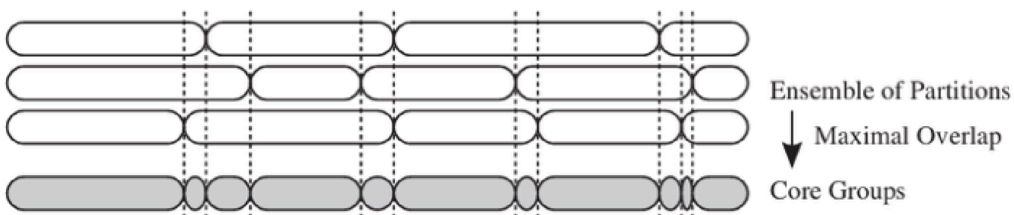
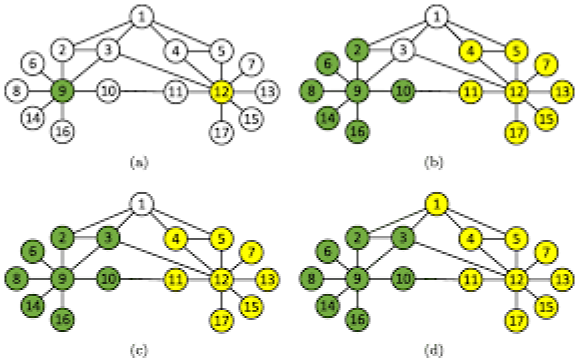


Fig. 1. In a core groups partition (bottom row) those vertices are in one group that are in the same community in all partitions of the ensemble (3 top rows).

Source: Fig 1 from [79]

Core Groups via Ensemble Learning. To make community detection more reliable on huge networks, the method introduces the concept of core groups, which are extracted before running the final community detection step. Rather than trusting a single partition of the graph, the approach generates an ensemble of partitions and then identifies nodes that repeatedly end up together across many runs. This repeated agreement is treated as strong evidence of a “true” underlying grouping. Nodes with high agreement are merged into core groups, which act as stable, high-confidence building blocks that simplify the graph and support scalable downstream clustering.



Source: Fig 2 from [81]

Label Propagation Step: How Core Groups Are Created. Core groups are built using repeated label propagation runs executed in parallel. Instead of assigning each node only one label, each node maintains a vector of labels that correspond to multiple label propagation instances. Across propagation steps, nodes update their label vectors based on their neighbors, causing labels to spread and gradually stabilize in densely connected regions. After several iterations, nodes that consistently share the same labels across many instances are grouped into core groups, reflecting high-confidence community “seeds.” The key benefit is that these core groups compress the graph, so the final community detection stage becomes much more scalable.

Algorithm 1: Hadoop Core Group Identification

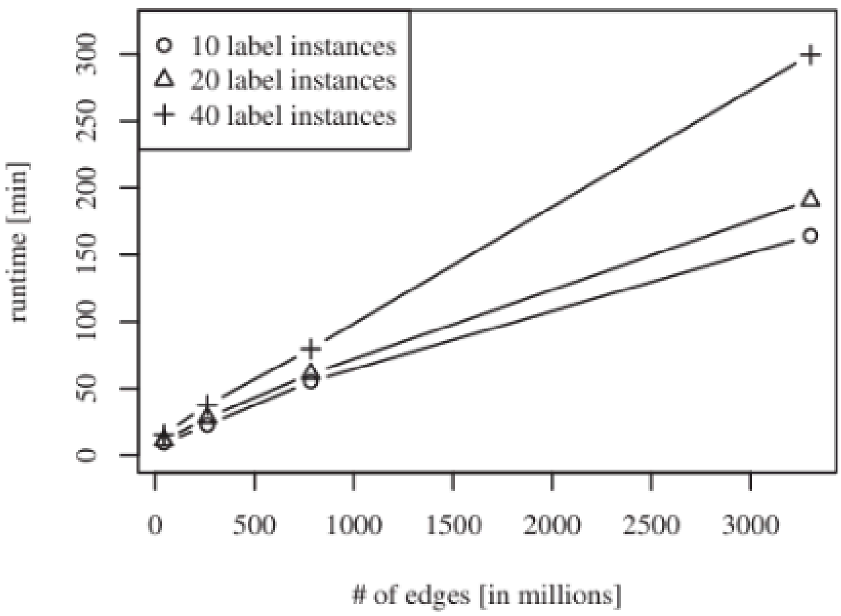
input : edgelist file $input\_file$, # of propagation steps p, # of label instances k

output: vertex-core group mapping file cg_file, edgelist file el_file

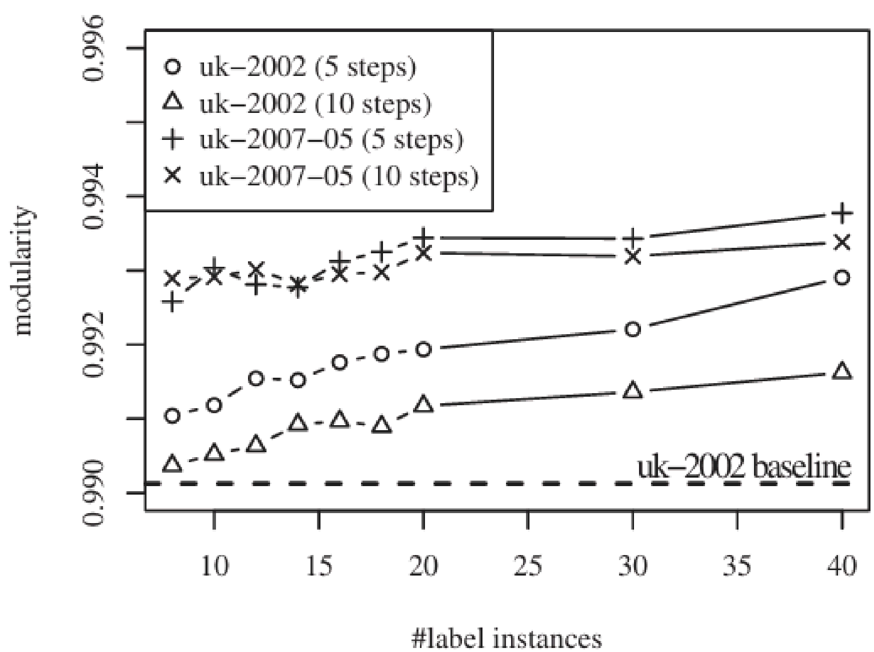
$passed\_labels \leftarrow$ `ReadMap` ($input\_file$, k)
for $i \leftarrow 1$ **to** $p - 1$ **do**
  $new\_labels \leftarrow$ `PropagateReduce` ($passed\_labels$)
  $passed\_labels \leftarrow$ `PropagateMap` (new_labels)
$final\_labels \leftarrow$ `CoreGroupsExportReduce` (new_labels, cg_file)
$final\_labels \leftarrow$ `EdgeListPreparationMap` ($final\_labels$)
$core\_group\_links \leftarrow$ `EdgeListPreparationReduce` ($final\_labels$)
$core\_group\_links \leftarrow$ `EdgeListExportMap` ($core\_group\_links$)
`EdgeListExportReduce` ($core\_group\_links$, el_file)

Source: Algorithm 1 from [79]

Hadoop/MapReduce Implementation of Core Group Identification. The paper outlines a Hadoop-based workflow that operationalizes this idea at scale. Given an edge list input, the system first initializes multiple label instances per node, then iteratively performs propagation using Reduce and Map stages to update labels over several steps. After propagation, the method exports a vertex-to-core-group mapping, then prepares a reduced edge list that connects core groups (rather than individual vertices). This produced core-group graph can be processed more efficiently by the final community detection algorithm, because the number of units being clustered is reduced while preserving strong structural signals from the original network.



Source: Fig 6 from [79]

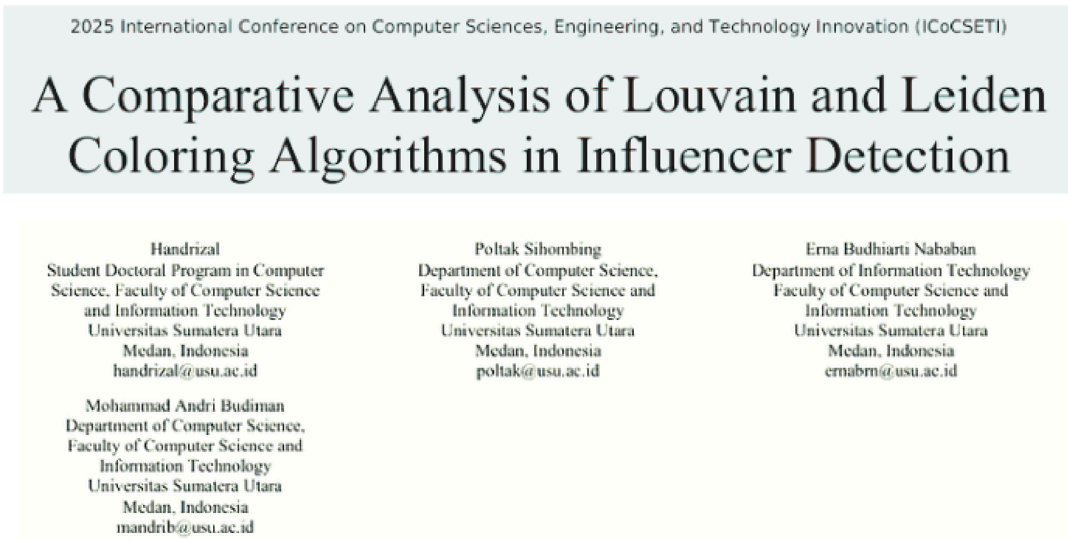


Source: Fig 5 from [79]

Scalability of Core Group Generation. The runtime behavior of core group generation is shown to scale predictably as graph size increases. Figure 6 demonstrates that runtime grows in a roughly linear manner as the number of edges increases, supporting the claim that the approach is scalable. The figure also highlights a cost–quality trade-off: increasing the number of label instances (for example, moving from 10 to 20 to 40 instances) increases runtime, since more parallel label information is being maintained and updated, but it can also improve the stability of the resulting core groups. The evaluation references both a symmetrized LiveJournal dataset (around 43 million edges) and a much larger uk-2005 dataset (around 0.9 billion edges), emphasizing the method's suitability for web-scale inputs.

Conclusion. Overall, the proposed distributed community detection method provides a scalable solution for processing extremely large networks by combining parallelism with core-group pre-processing. Core groups reduce the effective size of the graph before the final community detection stage, which improves feasibility on massive datasets. The reported modularity trends (Figure 5) indicate that varying the number of label instances and propagation steps affects quality, and the results are presented across different datasets and parameter settings, reinforcing that the approach can be tuned depending on the desired balance between runtime and community quality.

7.2 Community-Based Filtering in Social Media Search and Influencer Detection


2025 International Conference on Computer Sciences, Engineering, and Technology Innovation (ICoCSETI)

A Comparative Analysis of Louvain and Leiden Coloring Algorithms in Influencer Detection

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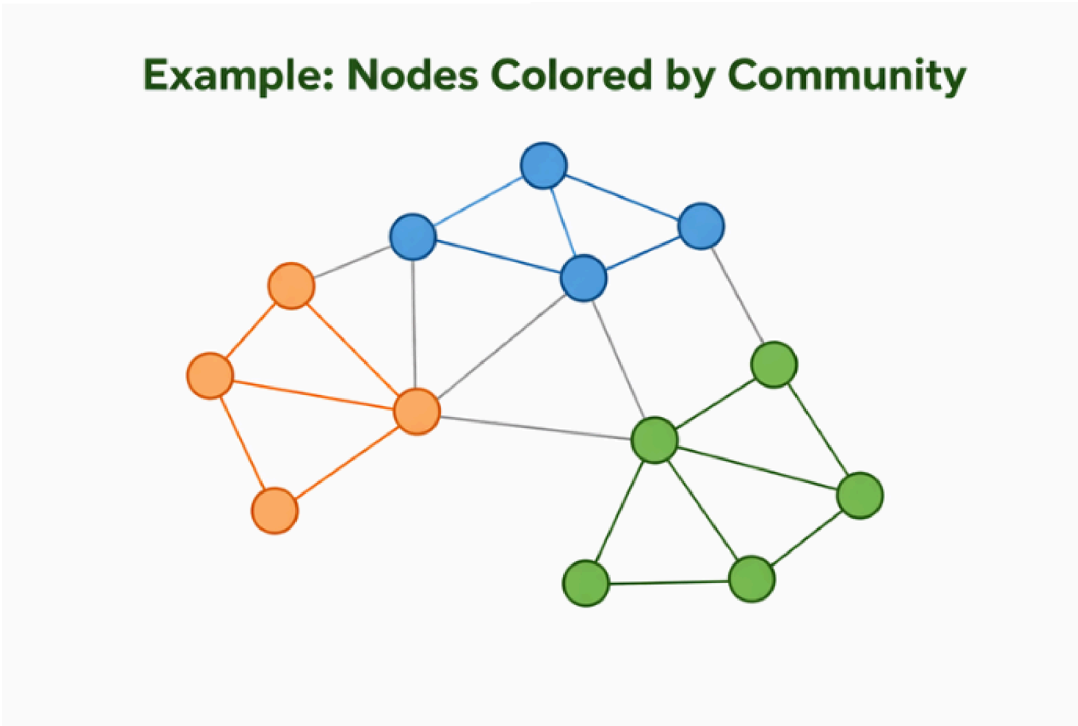
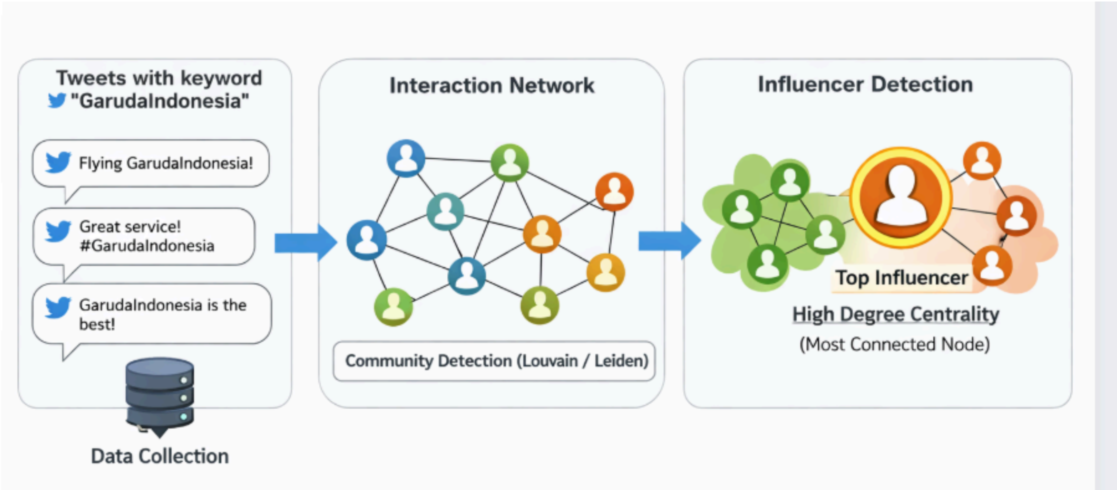
Source: [37]

Introduction to the Study. This 2025 study investigates influencer detection on Twitter (X) by combining community detection with graph-based ranking. The authors compare two workflows, “Louvain Coloring” and “Leiden Coloring,” where community detection is first performed using Louvain or Leiden and then communities are assigned distinct colors (labels) for clearer interpretation. Influencers are then identified by applying degree centrality within the detected community structure. The dataset is built by crawling tweets using the keyword “GarudaIndonesia” (22,623 rows), and the evaluation is performed using two random samples of 1,000 rows and 2,000 rows. The goal is to compare the two approaches using modularity (community quality), processing time, number of communities, and the resulting top-influencer ranking, since fast and reliable influencer detection is important for marketing and content distribution.



Source: AI generated Photo

Graph Coloring / Community Coloring Concept. In this paper, graph coloring does not mean solving the classic constraint “adjacent nodes must have different colors,” but rather assigning a unique color (label) to each detected community so the network structure is easier to interpret. The workflow is to first run Louvain or Leiden to obtain communities, then apply a community coloring step so every node inherits the color of its community. This makes large interaction graphs easier to read and helps organize downstream analysis because each node can be quickly associated with a specific community group through its label/color.



Source: AI generated Photo

Interaction Network and Influencers: Tweets including the selected keyword are gathered and turned into an interaction network, which represents users as nodes and the edges show the interactions such as mentions, replies, retweets, or likes. To find the user groups that communicate more intensively with each other than with the other parts of the network, community detection (Louvain or Leiden) is run**.**After communities are detected and colored, degree centrality is used to rank users inside the network (and practically, inside communities) to identify potential influencers, since users with higher degree centrality are connected to more users and can therefore spread information more widely within the interaction structure.

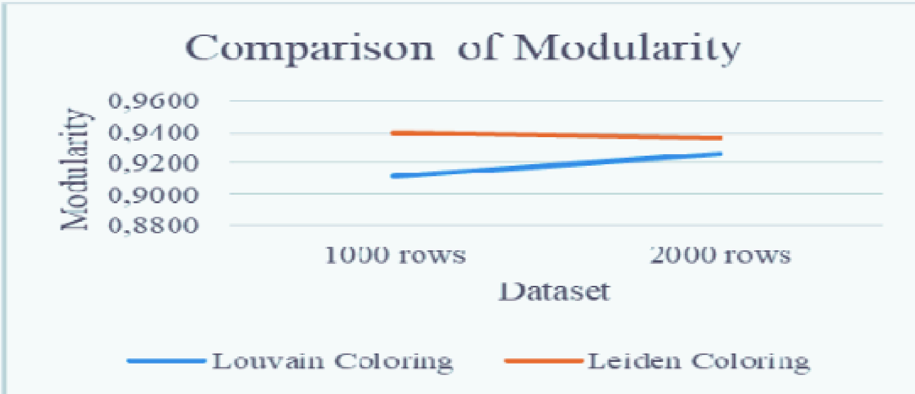


Fig. 4. Comparison of Matrix Modularity

Source: Fig 4 from [37]

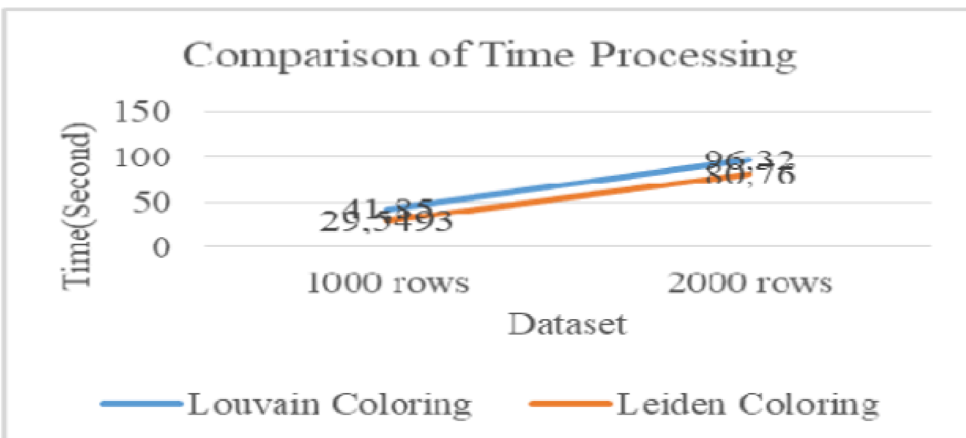


Fig. 5. Comparison of Matrix Processing Time

Source: Fig 5 from [37]

Dataset	Modularity	
	Louvain Coloring	Leiden Coloring
1000 rows	0.9114	0.9396
2000 rows	0.9259	0.9367
Average	0.9187	0.9383

Source: TABLE VIII from [37]

Methodology. The Leiden Coloring method follows a clear pipeline: Leiden is executed to detect communities, community coloring is applied so each community receives a unique label/color, and degree centrality is then computed to rank influential users (influencers). The same pipeline is applied using Louvain instead of Leiden to form the Louvain Coloring baseline. The two methods are compared using modularity to evaluate community quality, processing time to evaluate efficiency, and the number of detected communities to understand how fragmented or consolidated the output partition is, using the 1,000-row and 2,000-row samples from the crawled dataset.

Results and Key Findings : Higher modularity values appear for Leiden Coloring across both datasets, suggesting stronger community structure than what Louvain offers. As rows increase from a thousand to two thousand, Louvain rises from 0.9114 to 0.9259, while Leiden begins higher at 0.9396 before slipping a touch to 0.9367 - its average still lands at 0.9383, outpacing Louvain's 0.9187. Processing time falls more sharply with Leiden, clocking in around fifty-five seconds on average compared to almost sixty-nine for Louvain, which makes it roughly twenty percent faster here. The number of communities takes a different turn: Leiden produces fewer groups, implying wider, perhaps cleaner divisions. In smaller data sets, Louvain finds runs identify 936 clusters while only 565 are found by Leiden on the same data. Further, at the second size of this data, Louvain finds a whopping 1,800 communities while Leiden gives 934 establishing again its bigger chunk bias.

Conclusion. The study concludes that Leiden Coloring is more effective than Louvain Coloring for influencer detection on the evaluated Twitter (X) keyword dataset, because it provides higher modularity, lower processing time, and fewer detected communities. Using the "GarudaIndonesia" dataset, the combined approach of Leiden Coloring with degree centrality is reported to identify five recommended influencer accounts, supporting the idea that Leiden-based community detection can offer a stronger foundation for influencer ranking in large social interaction networks. Overall, the findings suggest that substituting

Louvain with Leiden in the community-detection stage can improve both the quality and efficiency of the influencer detection pipeline.

7.3 Enhancing community detection with weighted louvain

2025 11th International Conference on Web Research (ICWR)

Enhancing Community Detection with Weighted Louvain

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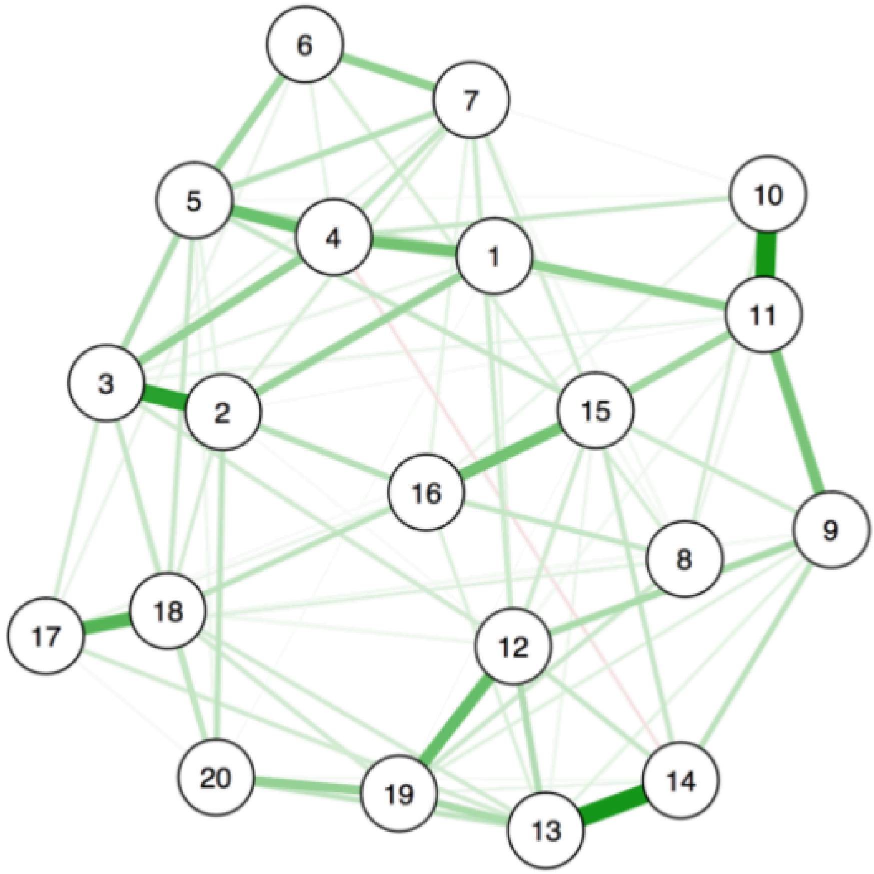
Source: [6]

Community Detection in Large Networks. This study proposes a Weighted Louvain variant for community detection, where edges carry weights so the algorithm can treat some relationships as stronger than others. Instead of assuming that all connections contribute equally, the method uses these weights during modularity optimization so strong ties have more influence on how communities form, while weak or noisy ties contribute less. The main objective is to improve community quality (measured by modularity) and to examine whether incorporating edge weights can also improve execution time. The proposed method is evaluated on multiple real-world networks and is compared against Louvain Base, Leiden, and Girvan–Newman.



Source: R tutorial: how to identify communities of items in networks | Psych Networks

Weighted Louvain: Strong vs. Weak Connections. A high, weight edge in a weighted network typically means that the two nodes share a strong relationship, while a low, weight edge indicates a weaker relationship. Weighted Louvain makes use of this by giving more power to strong edges to "drag" nodes into the same community together more strongly, while weak edges hardly affect merging or splitting communities**.**

TABLE II. PERFORMANCE COMPARISON OF COMMUNITY DETECTION ALGORITHMS

Dataset	*Algorithm*	*Modularity*	*Time (sec)*
Karate Club	Louvain_Base	0.4083	0.0043
	Louvain_Weighted	**0.4336**	**0.0033**
	Girvan-Newman	0.3928	0.0897
	Leiden	0.4198	0.0034
Dolphins	Louvain_Base	0.5224	0.0060
	Louvain_Weighted	**0.5297**	0.0050
	Girvan-Newman	0.5189	0.2613
	Leiden	0.5231	**0.0042**
Football	Louvain_Base	0.6044	0.0109
	Louvain_Weighted	**0.6101**	0.0097
	Girvan-Newman	0.5830	4.9230
	Leiden	0.6046	**0.0053**
Power	Louvain_Base	0.9804	0.2219
	Louvain_Weighted	**0.9898**	0.1588
	Girvan-Newman	0.9879	42.1487
	Leiden	0.9874	**0.0452**
Netscience	Louvain_Base	0.9519	0.1405
	Louvain_Weighted	**0.9598**	0.1314
	Girvan-Newman	0.9504	38.4299
	Leiden	0.9570	**0.1277**
Hep-th	Louvain_Base	0.9534	0.2200
	Louvain_Weighted	**0.9652**	0.1858
	Girvan-Newman	0.9355	145.4406
	Leiden	0.9542	**0.1389**

TABLE I. SUMMARY OF REAL-WORLD NETWORKS USED IN OUR EXPERIMENTS.

Dataset	*Nodes*	*Edges*	*Description*
Zachary's Karate Club	34	78	A small social network representing friendships among members of a university karate club. Commonly used for testing community detection methods.
Dolphin Social Network	62	159	A network of social interactions among dolphins in a marine habitat, based on their observed associations.
American College Football	115	613	A network of games played between college football teams during a single season, where teams are nodes and games form edges.
Power Grid	4,941	6,594	A network illustrating the structure of the US Western power grid, where nodes are power stations and edges represent transmission lines.
Netscience	1,589	2,742	A coauthorship network of researchers working on network science, with connections indicating joint publications.
Hep-th (High-Energy Theory)	8,361	15,751	A collaboration network of scientists in theoretical physics, based on coauthored research papers.

Source: TABLE II AND TABLE I from [6]

Experimental Setup and Datasets. The evaluation is conducted on six real-world networks with different sizes and domains, ranging from small social graphs to larger infrastructure and collaboration networks. The datasets include Zachary's Karate Club (34 nodes, 78 edges), Dolphin Social Network (62 nodes, 159 edges), American College Football (115 nodes, 613 edges), Power Grid (4,941 nodes, 6,594 edges), Netscience (1,589 nodes, 2,742 edges), and Hep-th (8,361 nodes, 15,751 edges). Performance is measured using modularity to represent community quality and execution time (in seconds) to represent efficiency, and results are reported consistently across all datasets for Louvain Base, Louvain Weighted, Girvan–Newman, and Leiden.

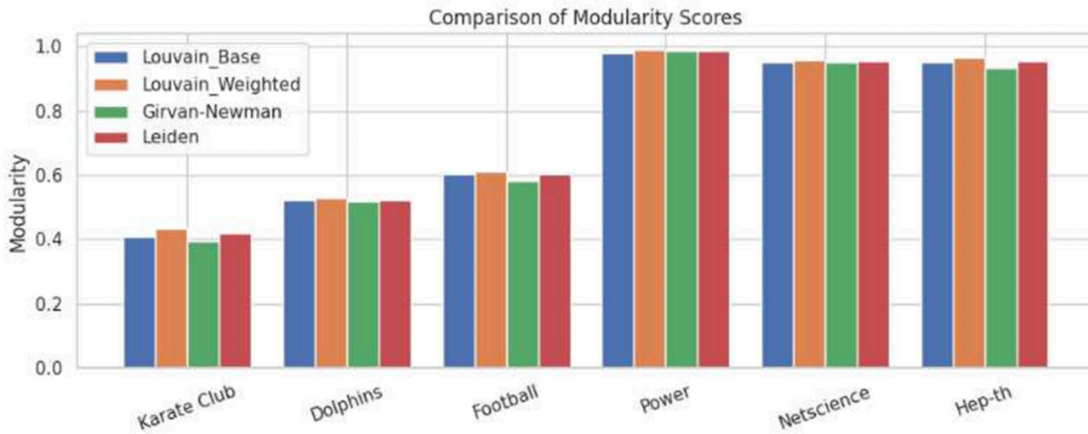


Fig. 1. Comparison of Modularity Scores across different datasets and algorithms.

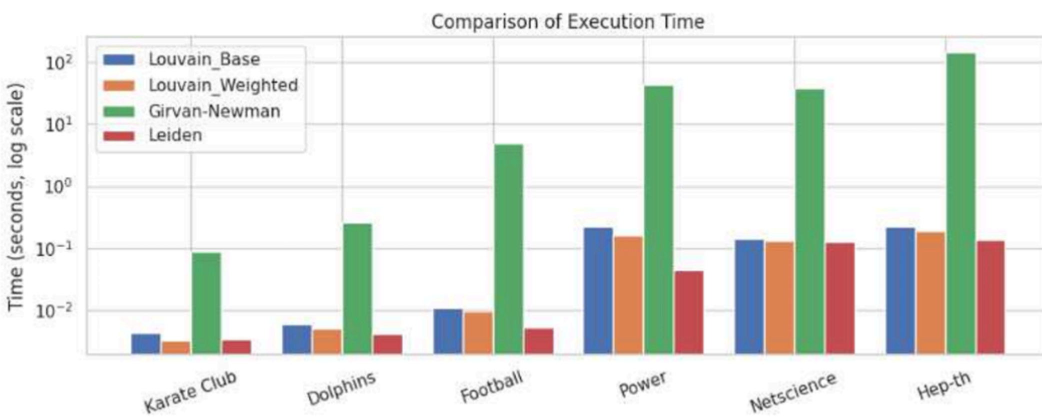


Fig. 2. Comparison of Execution Time for different algorithms.

Source: FIG 1 AND FIG 2 from [6]

Results and Key Findings. Weighted Louvain achieves the highest modularity of all methods compared to which it was tested across all datasets, showing consistent improvement over Louvain Base. For instance, on Karate Club, modularity is raised from 0.4083 (Louvain Base) to 0.4336 (Louvain Weighted), and runtime is slightly better from 0.0043 s to 0.0033 s. Similar modularity improvements are found on Dolphins (0.5224 to 0.5297), Football (0.6044 to 0.6101), Power Grid (0.9804 to 0.9898), Netscience (0.9519 to 0.9598), and Hep, th (0.9534 to 0.9652). Regarding runtime, Weighted Louvain is usually more efficient than Louvain Base on every dataset displayed, while GirvanNewman is slowest by a large margin consistently (for instance, 42.1487 s on Power Grid and 145.4406 s on Hep, th) and thus not suitable for larger networks. Leiden is in most cases the fastest overall (for example, 0.0452 s on Power Grid and 0.1389 s on Hep, th), but it does not always reach the modularity level of Weighted Louvain, which indicates a qualityspeed trade, off depending on the chosen method.

Conclusion. Overall, the paper demonstrates that adding edge weights to Louvain can consistently improve modularity and often reduce runtime compared to the original Louvain algorithm, while also dramatically outperforming Girvan–Newman in efficiency. The results suggest that algorithm choice should depend on the goal: Weighted Louvain is preferred when the priority is higher-quality communities (higher modularity), whereas Leiden is a strong choice when runtime is the main priority. The study also notes that future work would be stronger if edge weights were derived from real relationship strength (rather than assigned weights) and if the approach were tested on even larger graphs or implemented in parallel/distributed settings to further improve scalability.

7.4 Discussion

A recurring theme appears in all of these representative studies: In search-related systems, Louvain-based community detection is rarely employed as a stand-alone tool. Rather, it is integrated into more extensive pipelines that incorporate steps for preprocessing, weighting, or post-processing. Large graphs can be efficiently filtered, ranked, and explored thanks to community detection, which acts as a structural foundation. All three studies emphasize the same fundamental idea, even though different variations focus on scalability, quality, or stability: searching large networks becomes much more effective when the network is first organized into meaningful communities.

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