

Extraction and Classification of Dense Communities in the Web*

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ABSTRACT

The World Wide Web (WWW) is rapidly becoming important for society as a medium for sharing data, information and services, and there is a growing interest in tools for understanding collective behaviors and emerging phenomena in the WWW. In this paper we focus on the problem of searching and classifying *communities* in the web. Loosely speaking a community is a group of pages related to a common interest. More formally communities have been associated in the computer science literature with the existence of a locally dense sub-graph of the web-graph (where web pages are nodes and hyper-links are arcs of the web-graph). The core of our contribution is a new scalable algorithm for finding relatively dense subgraphs in massive graphs. We apply our algorithm on web-graphs built on three publicly available large crawls of the web (with raw sizes up to 120M nodes and 1G arcs). The effectiveness of our algorithm in finding dense subgraphs is demonstrated experimentally by embedding artificial communities in the web-graph and counting how many of these are blindly found. Effectiveness increases with the size and density of the communities: it is close to 100% for communities of a thirty nodes or more (even at low density). It is still about 80% even for communities of twenty nodes with density over 50% of the arcs present. At the lower extremes the algorithm catches 35% of dense communities made of ten nodes. We complete our *Community Watch* system by clustering the communities found in the web-graph into homogeneous groups by topic and labelling each group by representative keywords.

Categories and Subject Descriptors

F.2.2 [Nonnumerical Algorithms and Problems]: Computations on Discrete Structures; H.2.8 [Database Applications]: Data Mining; H.3.3 [Information Search and Retrieval]: Clustering

General Terms

Algorithms, Experimentation

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Keywords

Web graph, Communities, Dense Subgraph.

1. INTRODUCTION

Why are cyber-communities important?. Searching for social structures in the World Wide Web has emerged as one of the foremost research problems related to the breathtaking expansion of the World Wide Web. Thus there is a keen academic as well as industrial interest in developing efficient algorithms for collecting, storing and analyzing the pattern of pages and hyper-links that form the World Wide Web, since the pioneering work of Gibson, Kleinberg and Raghavan [19]. Nowadays many communities of the real world that want to have a major impact and recognition are represented in the Web. Thus the detection of *cyber-communities*, i.e. set of sites and pages sharing a common interest, improves also our knowledge of the world in general.

Cyber-communities as dense subgraphs of the web graph. The most popular way of defining cyber-communities is based on the interpretation of WWW *hyperlinks* as *social* links [10]. For example, the web page of a conference contains an hyper-link to all of its sponsors, similarly the home-page of a car lover contains links to all famous car manufactures. In this way, the Web is modelled by the *web graph*, a *directed graph* in which each vertex represents a web-page and each arc represents an hyper-link between the two corresponding pages. Intuitively, cyber-communities correspond to dense subgraphs of the web graph.

An open problem. Monika Henzinger in a recent survey on algorithmic challenges in web search engines [26] remarks that the Trawling algorithm of Kumar et al. [31] is able to enumerate dense bipartite graphs in the order of tens of nodes and states this open problem: “In order to more completely capture these cyber-communities, it would be interesting to detect much larger bipartite subgraphs, in the order of hundreds or thousands of nodes. They do not need to be complete, but should be dense, i.e. they should contain at least a constant fraction of the corresponding complete bipartite subgraphs. Are there efficient algorithms to detect them? And can these algorithms be implemented efficiently if only a small part of the graph fits in main memory?”

Theoretical results. From a theoretical point of view, the *dense k-subgraph* problem, i.e. finding the densest subgraph with k vertices in a given graph, is clearly NP-Hard (it is easy to see by a reduction from the max-clique problem). Some approximation algorithms with a non constant approximation factor can be found in the literature for example in [24, 14, 13], none of which seem to be of practical applicability. Studies about the inherent complexity of the problem of obtaining a constant factor approximation algorithm are reported in [25] and [12].

Some heuristic methods. In the literature there are a few heuristic methods to extract communities from the web (or from large graphs in general). The most important and ground breaking algorithm is due to Kumar et al. in [31] where the authors aim at enumerating complete bipartite subgraphs with very few vertices, then extend them to *dense bipartite subgraphs* by using local searches (based on the HITS ranking algorithm). The technique in [31] is aimed at detecting small complete bipartite communities, of the order of ten vertices, while the subsequent community expansion guided by the hub and authority scores of the HITS algorithm (regardless of further density considerations). In [16] Flake, Lawrence, Giles and Coetzee use the notion of maximum flow to extract communities, but they are also limited to communities for which an initial seed node is available. In [20] Gibson, Kumar and Tomkins use a new sampling method (shingling) based on the notion of min-wise independent permutations, introduced in [7], to evaluate the similarity of neighborhoods of vertices and then extract very large and very dense subgraphs of the web-host graph. This technique is specifically aimed to detecting very large and dense subgraphs, in a graph, like the web-host-graph of quite large average degree. The authors in [20, Section 4.2] remark that (with a reasonable set of parameters) the shingling method is effective for dense subgraphs of over 50 nodes but breaks down below 24 nodes. Thus there is room for improvements via alternative approaches.

Our contribution. In this paper we propose two new simple characterization of dense subgraphs. From these characterization we derive a new heuristic, which is based on a two-step filtering approach. In the first filtering step we estimate efficiently the average degree and the similarity of neighbor sets of vertices of a candidate community. This initial filtering is very efficient since it is based only on degree-counting. The second filtering step is based on an iterative refinement of the candidate community aimed at removing small degree vertices (relative to the target average density), and thus increasing the average degree of the remaining “core” community. We test our algorithm on very large snapshots of the web graph (both for the global web-graph and for some large national domains) and we give experimental evidence the effectiveness of the method. We have coupled the community extraction algorithm with a clustering tool that groups the communities found into homogeneous groups by topic and provide a useful user interface for exploring the community data. The user interface of the *Community Watch* system is publicly available at <http://comwatch.iit.cnr.it>. To the best of our knowledge this is the first publicly available tool to visualize cyber-communities.

Target size. In our method the user supplies a target threshold t and the algorithm lists all the communities found with average degree at least t . Naturally the lower the t -value the more communities will be found and the slower the method. In our experiments our method is still effective for values of t quite close to the average degree of the web-graphs (say within a factor 2), and communities of a few tens of nodes. Our heuristic is particularly efficient for detecting communities of large and medium size, while the method in [31] is explicitly targeted towards communities with a small complete bipartite core-set.

Final applications. The detection of dense subgraphs of the web-graph might serve as a stepping stone towards achieving several broader goals. One possible goal is to improve the performance of critical tools in the WWW infrastructure such as crawlers, indexing and ranking components of search engines. In this case often dense subgraphs are associated with negative phenomena such as the Tightly Knit Community (TKC) effect [34], link-farm spamming [23], and data duplication (mirroring) [2]. In this paper,

following [33] we place instead the accent on the “positive” aspect of cyber-communities: our intent at the moment is to provide an exploratory tool capable of extracting a synthetic description of the current status and current trends in the social structure of the WWW.

Visualization of the Communities. Given a single dense community it is easy by manual inspection to gain some hint as to its general area of interest and purpose, however gaining insight on hundreds (or thousands) of communities can become a tiresome task, therefore we have coupled our dense-subgraph extraction algorithm with a visualization tool that helps in the exploratory approach. This tool is based on the efficient clustering/labelling system described in detail in [17][18]. In nutshell from each community, using standard IR techniques, we extract a vector of representative words with weights related to the words frequencies (word-vector). A clustering algorithm is applied to the word-vectors and we obtain groups of communities that are homogeneous by topic, moreover a list of representative keywords for each cluster is generated so to guide the user to assess the intrinsic topic of each cluster of communities.

Mirrors and Link-farms. Information retrieval on the WWW is complicated by the phenomenon of “data replication” (mirroring) and several forms of spamming (e.g. link-farms). For mirrors, off-line detection of such structures using the techniques in [2] implies pairwise comparisons of all (or most if some heuristic filtering is used) pairs of web-sites, which is an expensive computations. Link-farm detection implies technique borderline with those used for community detection. In our context, however, efficiency and effectiveness of the community detection algorithm are not really impaired by such borderline phenomena. For this reason we do not attempt to filter out these phenomena before applying our algorithms. Instead we envision these steps (mirror detection and link-farm detection) as a post-processing phase in our *Community Watch* system. In particular since we perform efficiently both the community detection and community clustering we can apply mirror and link-farm detection separately and independently in each cluster thus retaining the overall system scalability.

2. PREVIOUS WORK

Given the hypertext nature of the WWW one can approach the problem of finding cyber-communities by using as main source the textual content of the web pages, the hyperlinks structure, or both. Among the methods for finding group of coherent pages based only on text content we can mention [8]. Recommendation systems usually collect information on social networks from a variety of sources (not only link structure) (e.g. [29]). Problems of a similar nature appears in the areas of social network analysis, citation analysis and bibliometrics, where however, given the relatively smaller data sets involved (relative to the WWW), efficiency is often not a critical issue [35].

Since the pioneering work [19] the prevailing trend in the Computer Science community is to use mainly the link-structure as basis of the computation. Previous literature on the problem of finding cyber-communities using link-based analysis in the web-graph can be broadly split into two large groups. In the first group are methods that need an initial seed of a community to start the process of community identification. Assuming the availability of a seed for a possible community naturally directs the computational effort in the region of the web-graph closest to the seed and suggests the use of sophisticated but computational intensive techniques, usually based of max-flow/min-cut approaches. In this category we can list the work of [19, 15, 16, 27, 28]. The second group of algorithms does not assume any seed and aims at finding all (or most) of the communities by exploring the

whole web graph. In this category falls the work of [31, 30, 36, 32, 20].

Certain particular artifacts in the WWW called “link farms” whose purpose is to bias search-engines pagerank-type ranking algorithms are a very particular type of “artificial” cyber-community that is traced using techniques bordering with those used to find dense subgraphs in general. See for example [37, 3].

Abello et al. [1] propose a method based on local searches with random restarts to escape local minima, which is quite computational intensive. A graph representing point to point telecommunications with 53 M nodes and 170M edges is used as input. The equipment used is a multiprocessor machine of 10 200MHz processors and total 6GB RAM memory. A timing result of roughly 36 hours is reported in [1] for an experiment handling a graph obtained by removing all nodes of degree larger than 30, thus, in effect, operating on a reduced graph of 9K nodes and 320K edges. Even discounting for the difference in equipment we feel that the method in [1] would not scale well to searching for medium-density and medium-size communities in graphs as large as those we are able to handle (up to 20M nodes and 180M edges after cleaning). Girvan and Newman [21] define a notion of local density based on counting the number of shortest paths in a graph sharing a given edge. This notion, though powerful, entails algorithm that do not scale well to the size of the web-graph. Spectral methods described in [9] also lack scalability (i.e. in [9] the method is applied to graphs from psychological experiments with 10K nodes and 70K edges).

A system similar in spirit to that proposed in this paper is *Campfire* described in [33] which is based on the Trawling algorithm for finding the dense core, on HITS for community expansion and on an indexing structure of community keywords that can be queried by the user. Our system is different from Campfire first of all in the algorithms used to detect communities but also in the final user interface: we provide a clustering/labelling interface that is suitable to giving a global view of the available data.

3. PRELIMINARIES

3.1 Notions and notation

A *directed graph* $G = (V, E)$ consists of a set V of *vertices* and a set E of *arcs*, where an arc is an ordered pair of vertices. The *web graph* is the directed graph representing the Web: vertices are pages and arcs are hyperlinks.

Let u, v be any vertices of a directed graph G , if there exists an arc $a = (u, v)$, then a is an *outlink* of u , and an *inlink* of v . Moreover, v is called a *successor* of u , and u a *predecessor* of v . For every vertex u , $N^+(u)$ denotes the set of its successors, and $N^-(u)$ the set of its predecessors. Then, the *outdegree* and the *indegree* of u are respectively $d^+(u) = |N^+(u)|$ and $d^-(u) = |N^-(u)|$. Let X by any subset of V , the successors and the predecessors of X are respectively defined by: $N^+(X) = \bigcup_{u \in X} N^+(u)$ and $N^-(X) = \bigcup_{u \in X} N^-(u)$. Observe that $X \cap N^+(X) \neq \emptyset$ is possible. A graph $G = (V, E)$ is called a *complete bipartite graph*, if V can be partitioned into two disjoint subsets X and Y , such that, for every vertex u of X , the set of successors of u is exactly Y , i.e., $\forall u \in X, N^+(u) = Y$. Consequently for every node $v \in Y$ its predecessor set is X . Finally, let $\tilde{N}(u)$ be the set of vertices that share at least one successor with u : $\tilde{N}(u) = \{w \in V \mid N^+(u) \cap N^+(w) \neq \emptyset\}$.

Two more useful definitions. Define for sets A and B the relation $A \simeq_\gamma B$ when $|A \cap B| \geq \gamma|B|$, for a constant γ . Define for positive numbers a, b the relation $a \approx b$ when $|a - b| \leq \epsilon|a|$, for a constant ϵ . When the constant can be inferred from the context the subscript is omitted.

3.2 Definitions of Web Community

The basic argument linking the (informal) notion of web communities and the (formal) notion of dense subgraphs is developed and justified in [31]. It is summarized in [31] as follows: “Web communities are characterized by dense directed bipartite subgraph”. Without entering in a formal definition of density in [31] it is stated the hypothesis that: “A random large enough and dense enough bipartite subgraph of the Web almost surely has a core”, (i.e. a complete bipartite sub-graph of size (i, j) for some small integer values, i and j). A standard definition of γ -density, as used for example in [20], is as follows: a γ -dense bipartite subgraph of a graph $G = (V, E)$ is a disjoint pair of sets of vertices, $X, Y \subseteq V$ such that $|\{(x, y) \in E \mid x \in X \wedge y \in Y\}| \geq \gamma|X||Y|$, for a real parameter $\gamma \in [0..1]$. Note that $\gamma|Y|$ is also a lower bound to the average out-degree of a node in X . Similarly a dense quasi-clique is a subset $X \subseteq V$ such that $|\{(x, y) \in E \mid x \in X \wedge y \in X\}| \geq \binom{|X|}{2}$, for a real parameter $\gamma \in [0..1]$, as in [1, 14]. This notion of a core of a dense subgraph in [31] is consistent with the notion of γ -density for values of γ large enough, where the notion of “almost surely”, (i, j) -core, “large enough”, “dense enough”, must be interpreted as a function of γ . Our formulation unifies the notion of a γ -dense bipartite subgraph and a γ -clique as a pair of not necessarily disjoint sets of vertices, $X, Y \subseteq V$ such that $\forall x \in X, |N^+(x) \cap Y| \geq \gamma|Y|$ and $\forall y \in Y, |N^-(y) \cap X| \geq \gamma'|X|$. For two constants γ and γ' . Our definition implies that in [20], and conversely, any γ -dense subgraph following [20] contains a γ -dense subgraph in our definition¹.

Thus a community in the web is defined by two sets of pages, the set of the Y *centers* of the community, i.e. pages sharing a common topic, and the set X of the *fans*, i.e., pages that are interested in the topic. Typically, every fan contains a link to most of the centers, at the same time, there are few links among centers (often for commercial reasons) and among fans (fans may not know each other).

4. HEURISTIC FOR LARGE DENSE SUBGRAPHS EXTRACTION

4.1 Description

The definition of γ -dense subgraph can be used to *test* if a pair of sets $X, Y \subseteq V$ is a γ -dense subgraph (both bipartite and clique). However it cannot be used to *find* efficiently a γ -dense subgraph (X, Y) embedded in G . In the following of this section we discuss a sequence of properties and then we will proceed by *relaxing* them up to the point of having properties that can be computed directly on the input graph G . These properties will hold exactly (with equality) for an *isolated* complete bipartite graph (and clique), will hold approximately for an *isolated* γ -dense graph, where the measure of approximation will be related to the parameter γ . However at the end we need a the final relaxation step in which we will consider the subgraphs as embedded in G .

4.1.1 Initial intuitive outline

First of all, let us give an initial intuition of the reason why our heuristic might work. Let $G = (V, E)$ be a sparse directed graph, and let (X, Y) be a γ -dense subgraph within G . Then, let u be any vertex of X . Since (X, Y) is a γ -dense subgraph by definition we have $\forall u \in X, N^+(u) \simeq_\gamma Y$, and symmetrically $\forall v \in Y, N^-(v) \simeq_{\gamma'} X$. For values $\gamma > 0.5$ the pigeon hole principle ensures that any two nodes u and v of X always share a successor in Y , thus $X \subseteq \tilde{N}(u)$,

¹It is sufficient to eliminate nodes of X of outdegree smaller than $\gamma|Y|$, and from Y those of indegree smaller than $\gamma'|X|$.

and, if every vertex of Y has at least a predecessor in X , also $Y \subseteq N^+(\tilde{N}(u))$. The main idea now is to estimate quickly, for every vertex u of G , the degree of similarity of $N^+(u)$ and $N^+(\tilde{N}(u))$. In the case of an isolated complete bipartite graph $N^+(u) = Y$, and $N^+(\tilde{N}(u)) = Y$. For an isolated γ -dense bipartite graph, we have $N^+(u) \simeq_\gamma Y$ and $N^+(\tilde{N}(u)) = Y$. The conjecture is that when the γ -dense bipartite graph is a subgraph of G , and thus we have the weaker relationship $Y \subseteq N^+(\tilde{N}(u))$, the excess $N^+(\tilde{N}(u)) \setminus Y$ is small compared to Y so to make the comparison of the two sets still significant for detecting the presence of a dense subgraph.

4.1.2 The isolated complete case

To gain in efficiency, instead of evaluating the similarity of successor set, we will estimate the similarity of out-degrees by counting. In a complete bipartite graph (X, Y) , we have that $\forall u \in X$, $N^+(u) = Y$, therefore, $\forall u, v \in X$, $N^+(u) = N^+(v)$. The set of vertices sharing a successor with u is $\tilde{N}(u) = X$, and moreover $N^+(\tilde{N}(u)) = Y$. Passing from relations among sets to relations among cardinalities we have that: $\forall u, v \in X$, $d^+(u) = d^+(v)$, and the degree of any node coincide with the average out-degree:

$$d^+(u) = \frac{1}{|\tilde{N}(u)|} \sum_{v \in \tilde{N}(u)} d^+(v).$$

4.1.3 The isolated γ -dense case

In a γ -dense bipartite graph, we still have $\tilde{N}(u) = X$ but now, $|Y| \geq d^+(v) \geq \gamma|Y|$ for every $v \in X$. Thus we can conclude that

$$|d^+(u) - \frac{1}{|\tilde{N}(u)|} \sum_{v \in \tilde{N}(u)} d^+(v)| \leq (1 - \gamma)|Y| \leq \frac{1 - \gamma}{\gamma} d^+(u).$$

For $\gamma \rightarrow 1$ the difference tends to zero. Finally assuming that for a γ -dense bipartite subgraph of G the excesses $\tilde{N}(u) \setminus X$ and $N^+(\tilde{N}(u)) \setminus Y$ give a small contribution, we can still use the above test as evidence of the presence of a dense subgraph. At this point we pause, we state our first criterion and we subject it to criticism in order to improve it.

CRITERION 1. *If $d^+(u)$ and $|\tilde{N}(u)|$ are big enough and*

$$d^+(u) \approx \frac{1}{|\tilde{N}(u)|} \sum_{v \in \tilde{N}(u)} d^+(v),$$

then $(\tilde{N}(u), N^+(\tilde{N}(u)))$ might contain a community.

4.1.4 A critique of Criterion 1

Unfortunately, this criterion 1 cannot be used yet in this form. One reason is that computing $\tilde{N}(u)$ for every vertex u of big enough outdegree in the web graph G is not scalable. Moreover, the criterion is not robust enough w.r.t. noise from the graph. Assume that the situation depicted in figure 1 occurs: $u \in X$, (X, Y) induces a complete bipartite graph with $|Z| = |X| = |Y| = x$, and each vertex of Y has one more predecessor of degree 1 in Z . Then, $\tilde{N}(u) = X \cup Z$, so $\frac{1}{|\tilde{N}(u)|} \sum_{v \in \tilde{N}(u)} d^+(v) = \frac{x+1}{2}$ that is far from $d^+(u) = x$, so (X, Y) will not be detected.

4.1.5 Overcoming the drawbacks of Criterion 1

Because of the shortcomings of Criterion 1 we describe a second criterion that is more complex to derive but computationally more effective and robust. As before we will

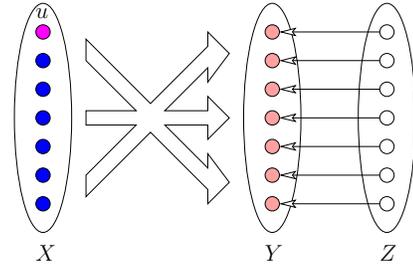


Figure 1: A complete bipartite subgraph with $|X| = |Y| = x$, and some “noise”.

start with the case of the isolated complete bipartite graph. Consider a node $u \in X$, clearly $N^+(u) = Y$, and $\forall y \in N^+(u)$, $N^-(y) = X$, thus $\forall w \in N^-(y)$, $N^+(w) = Y$. Turning to the cardinalities: for a node $u \in X$, $\forall y \in N^+(u)$, $\forall w \in N^-(y)$ $d^+(w) = |Y|$. Thus also the average value of all out-degrees for nodes in $N^-(y)$ is $|Y|$. In formulae: given $u \in X$, $\forall y \in N^+(u)$,

$$\frac{1}{d^-(y)} \sum_{w \in N^-(y)} d^+(w) = |Y|.$$

Next we average over all $y \in N^+(u)$ by obtaining the following equation: given $u \in X$,

$$\frac{1}{\sum_{y \in N^+(u)} d^-(y)} \sum_{y \in N^+(u)} \sum_{w \in N^-(y)} d^+(w) = |Y|.$$

Finally since $d^+(u) = |Y|$ we have the equality:

$$\frac{1}{\sum_{y \in N^+(u)} d^-(y)} \sum_{y \in N^+(u)} \sum_{w \in N^-(y)} d^+(w) = d^+(u).$$

Next we see how to transform the above equality for isolated γ -dense graphs. Consider a node $u \in X$, now $N^+(u) \simeq_\gamma Y$, and for a node $v \in Y$, $N^-(v) \simeq_{\gamma'} X$. Thus we get the bounds:

$$|X||Y| \geq \sum_{y \in N^+(u)} d^-(y) \geq \gamma|Y|\gamma'|X|,$$

$$|Y|^2|X| \geq \sum_{y \in N^+(u)} \sum_{w \in N^-(y)} d^+(w) \geq \gamma^2|Y|^2\gamma'|X|.$$

Thus the ratio of the two quantities is in the range $[\frac{|Y|}{\gamma\gamma'}, |Y|\gamma^2\gamma']$. On the other hand $|Y| \geq d^+(u) \geq \gamma|Y|$. Therefore the difference of the two terms is bounded by $|Y|\frac{1-\gamma^2\gamma'}{\gamma\gamma'}$, which is bounded by $d^+(u)\frac{1-\gamma^2\gamma'}{\gamma^2\gamma'}$. Again for $\gamma \rightarrow 1$ and $\gamma' \rightarrow 1$ the difference tends to zero.

Thus in an approximate sense the relationship is preserved for isolated γ -dense bipartite graphs. Clearly now we will make a further relaxation by considering the sets $N^+(\cdot)$ and $N^-(\cdot)$ as referred to the overall graph G , instead of just the isolated pair (X, Y) .

CRITERION 2. *If $d^+(u)$ and $|\tilde{N}(u)|$ are big enough and*

$$d^+(u) \approx \frac{1}{\sum_{y \in N^+(u)} d^-(y)} \sum_{y \in N^+(u)} \sum_{w \in N^-(y)} d^+(w),$$

then $(\tilde{N}(u), N^+(\tilde{N}(u)))$ might contain a community.

4.1.6 Advantages of Criterion 2

There are several advantages in using Criterion 2. The first advantage is that the relevant summations are defined over sets $N^+(\cdot)$ and $N^-(\cdot)$ that are encoded directly in the graphs G and G^T . We will compute $\tilde{N}(u)$ in the second phase only for vertices that are likely to belong to a community. The second advantage is that the result of the inner summation can be pre-computed stored and reused. We just need to store two tables of size n ($n = |V|$), one containing the values of $\sum_{v \in N^-(w)} d^+(v)$, the other containing the in-degrees. Thirdly, the criterion 2 is much more robust than criterion 1 to noise, since the outdegree of every vertex of X is counted many times. For example, in the situation depicted in figure 1, we obtain the following result:

$$\forall u \in X \text{ and } w \in N^+(u), \sum_{v \in N^-(w)} d^+(v) = x^2 + 1.$$

Thus, $\forall u \in X$,

$$\frac{1}{\sum_{w \in N^+(u)} d^-(w)} \sum_{w \in N^+(u)} \sum_{v \in N^-(w)} d^+(v) = \frac{x(x^2+1)}{x(x+1)} \simeq x.$$

4.1.7 Final refinement step

Finally, let u be a vertex that satisfies the criterion 2, we construct explicitly the two sets $\tilde{N}(u)$ and $N^+(\tilde{N}(u))$. Then, we extract the community (X, Y) contained in $(\tilde{N}(u), N^+(\tilde{N}(u)))$ thanks to an iterative loop in which we remove from $\tilde{N}(u)$ all vertices v for which $N^+(v) \cap N^+(\tilde{N}(u))$ is small, and we remove from $N^+(\tilde{N}(u))$ all vertices w for which $N^-(w) \cap \tilde{N}(u)$ is small.

4.2 Algorithms

In figures 2 and 3 we give the pseudo-code for our heuristic. Algorithm RobustDensityEstimation detects vertices that satisfy the filtering formula of criterion 2, then function ExtractCommunity computes $\tilde{N}(u)$ and $N^+(\tilde{N}(u))$ and extracts the community of which u is a fan. This two algorithms are a straightforward application of the formula in the criterion 2.

4.3 Handling of overlapping communities

Our algorithm can capture also partially overlapping communities. This case may happen when we have older communities that are in the process of splitting or newly formed communities in the process of merging. However overlapping centers and overlapping fans are treated differently, since the algorithm is not fully symmetric in handling fans and centers.

Communities sharing fans. The case depicted in Figure 4(a) is that of overlapping fans. If the overlap $X \cap X'$ is large with respect to $X \cup X'$ then our algorithm will just return the union of the two communities $(X \cup X', Y \cup Y')$. Otherwise when the overlap $X \cap X'$ is not large the algorithm will return two communities: either the pairs (X, Y) and $(X' \setminus X, Y')$, or the pairs (X', Y') and $(X \setminus X', Y)$. So we will report both the communities having their fan-sets overlapping, but the representative fan sets will be split. The notion of large/small overlap is a complex function of the degree threshold and other parameters of the algorithm. In either case we do not miss any important structure of our data.

Communities sharing centers. Note that the behavior is different in the case of overlapping centers. A vertex can be a center of several communities. Thus, in the case depicted in Figure 4(b), if the overlap $Y \cap Y'$ is big with respect to $Y \cup Y'$, then we will return the union of the two communities $(X \cup X', Y \cup Y')$, otherwise we will return exactly the two overlapping communities (X, Y) and (X', Y') . In either

Algorithm RobustDensityEstimation

Input: A directed graph $G = (V, E)$, a threshold for degrees
Result: A set S of dense subgraphs detected by vertices of outdegrees $>$ threshold

```

begin
  Init:
  forall  $u$  of  $G$  do
    forall  $v \in N^-(u)$  do
      TabSum[ $u$ ]  $\leftarrow$  TabSum[ $u$ ] +  $d^+(v)$ 
    end
  end
  Search:
  forall  $u$  that is not already a fan of a community and
  s.t.  $d^+(u) >$  threshold do
    sum  $\leftarrow$  0;
    nb  $\leftarrow$  0;
    forall  $v \in N^+(u)$  do
      sum  $\leftarrow$  sum + TabSum[ $v$ ];
      nb  $\leftarrow$  nb +  $d^-(v)$ ;
    end
    if sum/nb  $\simeq$   $d^+(u)$  and nb  $>$   $d^+(u) \times$ 
    threshold then
       $S \leftarrow S \cup$  ExtractCommunity( $u$ );
    end
  end
  Return  $S$ ;
end

```

Figure 2: RobustDensityEstimation performs the main filtering step.

case we do not miss any important structure of our data. Observe that the last loop of function ExtractCommunity removes *logically* from the graph all arcs of the current community, but not the vertices. Moreover, a vertex can be fan of a community and center of several communities. In particular it can be fan and center for the same community, so we are able to detect dense quasi bipartite subgraphs as well as quasi cliques.

4.4 Complexity analysis

We perform now a semi-empirical complexity analysis in the standard RAM model. The graph G and its transpose G^T are assumed to be stored in main memory in such a way as to be able to access a node in time $O(1)$ and links incident to it in time $O(1)$ per link. We need $O(1)$ extra storage per node to store in-degree, out-degree, a counter TabSum, and a tag bit. Algorithm RobustDensityEstimation visits each edge at most once and performs $O(1)$ operations for each edge, thus has a cost $O(|V| + |E|)$, except for the cost of invocations of the ExtractCommunity function. Potentially the total time cost of the invocations of ExtractCommunity is large, however experimentally the time cost grows only linearly with the number of communities found. This behavior can be explained as follows. We measured that less than 30% of the invocations do not result in the construction of a community (see Table 5), and that the inner refinement loop converges on average in less than 3 iterations (see Table 4). If the number of nodes and edges of a community found by ExtractCommunity for u is proportional by a constant to the size of the bipartite sub-graph $(\tilde{N}(u), N^+(\tilde{N}(u)))$ then we are allowed to charge all operations within invocations of ExtractCommunity to the size of the output. Under these conditions each edge is charged on average a constant number of operations, thus explaining the observed overall behavior $O(|V| + |E| + |Output|)$.

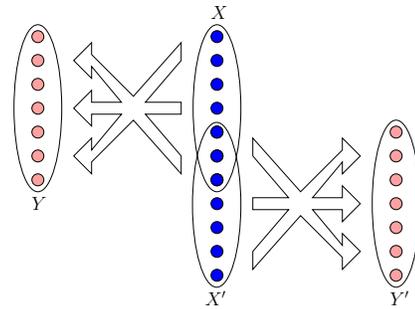
Function ExtractCommunity
Input: A vertex u of a directed graph $G = (V, E)$. Slackness parameter ϵ
Result: A community of which u is a fan
begin
 Initialization:
 forall $v \in N^+(u)$ **do**
 forall $w \in N^-(v)$ that is not already a fan of a community **do**
 if $d^+(w) > (1 - \epsilon)d^+(u)$ **then** mark w as potential fan
 end
 end
 forall potential fan v **do**
 forall $w \in N^+(v)$ **do**
 mark w as potential center;
 end
 end
 Iterative refinement:
 repeat
 Unmark potential fans of small local outdegree;
 Unmark potential centers of small local indegree;
 until Number of potential fans and centers have not changed significantly
 Update global data structures:
 forall potential fan v **do**
 forall $w \in N^+(v)$ that is also a potential center **do**
 TabSum[w] \leftarrow TabSum[w] - $d^+(v)$;
 $d^-(w) \leftarrow d^-(w) - 1$;
 end
 end
 Return (potential fans, potential centers);
end

Figure 3: ExtractCommunity extracts the dense subgraph.

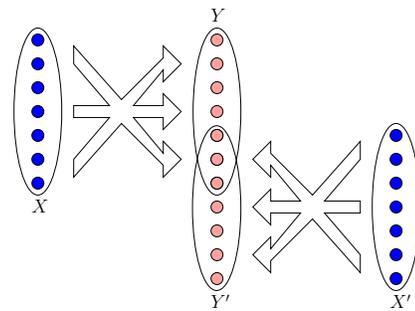
4.5 Scalability

The algorithm we described, including the initial cleaning steps, can be easily converted to work in the streaming model, except for procedure ExtractCommunity that seems to require the use of random access of data in core memory. Here we want to estimate with a “back of the envelope” calculation the limits of this approach using core memory. Andrei Broder et al. [6] in the year 2000 estimated the size of the indexable web graph at 200M pages and 1.5G edges (thus an average degree about 7.5 links per page, which is consistent with the average degree 8.4 of the WebBase data of 2001). A more recent estimate by Gulli and Signorini [22] in 2005 gives a count of 11.5G pages. The latest index-size war ended with Google claiming an index of 25G pages. The average degree of the webgraph has been increasing recently due to the dynamic generation of pages with high degree, and some measurements give a count of 40.² The initial cleaning phase reduces the WebBase graph by a factor 0.17 in node count and 0.059 in the Edge count. Thus using these coefficients the cleaned web graph might have 4.25G nodes and 59G arcs. The compression techniques in [5] for the WebBase dataset achieves an overall performance of 3.08 bits/edge. These coefficient applied to our cleaned web graph give a total of 22.5Gbytes to store the graph. Storing the graph G and its transpose we need to double the storage (although here some saving might be achieved), thus achieving an estimate of about 45Gbytes. With current technology this amount of core memory can certainly be provided by state of the art multiprocessors mainframes

²S. Vigna and P. Boldi, personal communication.



(a) Communities sharing fans



(b) Communities sharing centers

Figure 4: Two cases of community intersection

(e.g IBM System Z9 sells in configurations ranging from 8 to 64 GB of RAM core memory).

5. TESTING EFFECTIVENESS

By construction algorithms RobustDensityEstimation and ExtractCommunity return a list of dense subgraph (where size and density are controlled by the parameters t and ϵ). Using standard terminology in Information Retrieval we can say that full precision is guaranteed by default. In this section we estimate the recall properties of the proposed method. This task is complex since we have no efficient alternative method for obtaining a guaranteed ground truth. Therefore we proceed as follows. We add some arcs in the graph representing the Italian domain of the year 2004, so to create new dense subgraphs. Afterwards, we observe how many of these new “communities” are detected by the algorithm that is run blindly with respect to the artificially embedded community. The number of edges added is of the order of only 50,000 and it is likely that the nature of a graph with 100M edges is not affected.

In the first experiment, about detecting bipartite communities, we introduce 480 dense bipartite subgraphs. More precisely we introduce 10 bipartite subgraphs for each of the 48 categories representing all possible combinations of number of fans, number of centers, and density over a number of fans is chosen in $\{10, 20, 40, 80\}$; number of centers chosen in $\{10, 20, 40, 80\}$; and density randomly chosen in the ranges $[0.25, 0.5]$ (low), $[0.5, 0.75]$ (medium), and $[0.75, 1]$ (high).

Moreover, the fans and centers of every new community are chosen so that they don’t intersect any community found in the original graph nor any other new community. The following table (Table 1) shows how many added communities

are found in average over 53 experiments. For every one of the 48 types, the maximum recall number is 10.

# Centers	80	0	5.2	9.6	10	1.2	8.4	9.7	10	5.7	8.6	9.5	9.8
	40	0	5.4	9.5	9.9	0.7	8	9.7	9.9	5.4	8.6	9.7	9.8
	20	0	2.7	5.4	6	0.9	7.9	9.6	9.9	4.6	8.4	9.6	9.9
	10	0	0	0	0	0.1	0.8	1.9	3.2	3.3	6.5	9	9.7
	10	20	40	80	10	20	40	80	10	20	40	80	
	# of Fans				# of Fans				# of Fans				
	Low density				Med. density				High density				

Table 1: Number of added bipartite communities found with threshold=8 depending on number of fans, centers, and density.

In the second experiment, about detecting cliques, we introduce ten cliques for each of 12 classes representing all possible combinations over: number of pages in {10, 20, 30, 40}, and density randomly chosen in the ranges [0.25, 0.5], [0.5, 0.75], and [0.75, 1]. The following table (Table 2) shows how many such cliques are found in average over 70 experiments. Again the maximum recall number per entry is 10.

# Pages	40	9.6	9.8	9.7
	30	8.5	9.4	9.3
	20	3.6	7.6	8.3
	10	0	0.1	3.5
	Low	Med	High	
	Density			

Table 2: Number of added clique communities found with threshold=8 depending on number of pages and density.

The cleaned .it 2004 graph used for the test has an average degree roughly 6 (see Section 6). A small bipartite graph of 10-by-10 nodes or a small clique of 10 nodes at 50% density has an average degree of 5. The breakdown of the degree-counting heuristic for these low thresholds is easily explained with the fact that these small and sparse communities are effectively hard to distinguish from the background graph by simple degree counting.

6. LARGE COMMUNITIES IN THE WEB

In this section we apply our algorithm to the task of extracting and classifying real large communities in the web.

6.1 Data set

For our experiments we have used data from The Stanford WebBase project [11] and data from the Web-Graph project [5, 4]. Raw data is publicly available at <http://law.dsi.unimi.it/>. More precisely we apply our algorithm on three graphs: the graph that represents a snapshot of the Web of the year 2001 (118M pages and 1G links); the graph that represents a snapshot of the Italian domain of the year 2004 (41M pages and 1.15G arcs); the graph that represents a snapshot of the United Kingdom domain of the year 2005 (39M pages and 0.9G links).

Since we are searching communities by the study of social links, we first remove all *nepotistic links*, i.e., links between two pages that belong to the same domain (this is a standard cleaning step used also in [31]). Once these links are removed, we remove also all *isolated* pages, i.e., pages with both outdegree and indegree equal to zero. Observe that we don't remove anything else from the graph, for example we

don't need to remove small outdegree pages and large indegree pages, as it is usually done for efficiency reasons, since our algorithm handles these cases efficiently and correctly. We obtain the reduced data sets shown in Table 3.

Web 2001	20.1M pages	59.4M links	av deg 3
.it 2004	17.3M pages	104.5M links	av deg 6
.uk 2005	16.3M pages	183.3M links	av deg 11

Table 3: The reduced data sets. Number of nodes, edges and average degree.

6.2 Communities extraction

Figure 5 presents the results obtained with the three graphs presented before. The y axis shows how many communities are found, and the x axis represents the value of the parameter threshold. Moreover communities are partitioned by density into four categories (shown in grey-scale) corresponding to density intervals: [1,0.75], [0.75, 0.5], [0.5, 0.25], [0.25, 0.00].

Table 4 reports the time needed for the experiments with an Intel Pentium IV 3.2 Ghz single processor computer using 3.5 GB RAM memory. The data sets, although large, were in a cleverly compressed format and could be stored in main memory. The column “# loops” shows the average number of iterative refinement done for each community in Algorithm ExtractCommunity. Depending on the fan out degree threshold, time ranges from a few minutes to just above two hours for the most intensive computation. Table 5 shows the effectiveness of the degree-based filter since in the large tests just only 6% to 8% of the invocations to ExtractCommunity do not return a community. Note that this false-positive rate of the first stage does not impact much on the algorithm's efficiency nor on the effectiveness. The false positives of the first stage are caught anyhow by the second stage.

Interestingly in Table 7 it is shown the coverage of the communities with respect to the nodes of sufficiently high degree. In two national domains the percentage of nodes covered by a community is above 90% for national domains, and just below 60% for the web graph (of 2001). Table 6 shows the distribution of size and density of communities found. The web 2001 data set seems richer in communities with few fans (range [10-25]) and poorer in communities with many fans (range ≥ 100) and this might explain the lower coverage.

Thresh.	Web 2001		Italy 2004		Uk 2005	
	Num.	perc.	Num.	perc.	Num.	perc.
10	364	6%	34	3%	377	8%
15	135	5%	24	5%	331	14%
20	246	18%	24	9%	526	30%
25	148	19%	4	3%	323	30%

Table 5: Number and percentage of useless calls to ExtractCommunity.

Table 6 shows how many communities are found with the threshold equal to 10, in the three data sets in function of number of fans, centers, and density. Low, medium and high densities are respectively the ranges [0.25, 0.5], [0.5, 0.75], and [0.75, 1].

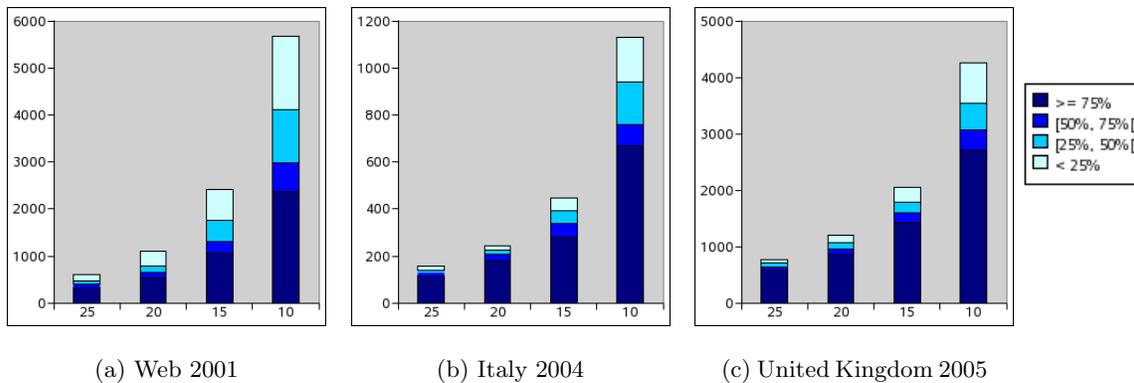


Figure 5: Number of communities found by Algorithm RobustDensityEstimation as a function of the degree threshold. The gray scale denotes a partition of the communities by density.

Thresh.	Web 2001			Italy 2004			Uk 2005		
	# com.	# loops	Time	# com.	# loops	Time	# com.	# loops	Time
10	5686	2.7	2h12min	1099	2.7	30min	4220	2.5	1h10min
15	2412	2.8	1h03min	452	2.8	17min	2024	2.6	38min
20	1103	2.8	31min	248	2.8	10min	1204	2.7	27min
25	616	2.6	19min	153	2.8	7min	767	2.7	20 min

Table 4: Measurements of performance. Number of communities found, total computing time and average number of cleaning loops per community.

7. VISUALIZATION OF COMMUNITIES

The compressed data structure in [5] storing the web graph does not hold any information about the textual content of the pages. Therefore, once the list of url’s of fans and centers for each community has been created, a non-recursive crawl of the WWW focussed on this list of url’s has been performed in order to recover textual data from communities.

What we want is to obtain an approximate description of the community topics. The intuition is that the topic of a community is well described by its centers. As good summary of the content of a center page we extract the text contained in the title tag of the page. We treat fan pages in a different way. The full content of the page is probably not interesting because a fan page can contain different topics, or might even be part of different communities. We extract only the anchor text of the link to a center page because it is a good textual description of the edge from the fan to a center in the community graph. For each community we build a weighted set of words getting all extracted words from centers and fans. The weight of each word takes into account if a word comes from a center and/or a fan and if it is repeated. All the words in a stop word list are removed. We build a flat clustering of the communities. For clustering we use the k-center algorithm described in [18, 17]. As a metric we adopt the Generalized Jaccard distance (a weighted form of the standard Jaccard distance).

This paper focusses on the algorithmic principles and testing of a fast and effective heuristic for detecting large-to-medium size dense subgraphs in the web graph. The examples of clusters reported in this section are to be considered as anecdotal evidence of the capabilities of the Community Watch System. We plan on using the Community Watch tool for a full-scale analysis of portions of the Web Graph

as future research. In Table 8 we show some high quality clusters of community found by the Community Watch tool in the data-set UK2005 among those communities detected with threshold $t = 25$ (767 communities). Further filtering of communities with too few centers reduces the number of items (communities) to 636. The full listing can be inspected by using the Community Watch web interface publicly available at <http://comwatch.iit.cnr.it>.

8. CONCLUSIONS AND FUTURE WORK

In this paper we tackle the problem of finding dense subgraphs of the web-graph. We propose an efficient heuristic method that is shown experimentally to be able to discover about 80% of communities having about 20 fans/centers, even at medium density (above 50%). The effectiveness increases and approaches 100% for larger and denser communities. For communities of less than 20 fans/centers (say 10 fans and 10 centers) our algorithm is still able to detect a sizable fraction of the communities present (about 35%) whenever these are at least 75% dense. Our method is effective for a medium range of community size/density which is not well detected by the current technology. One can cover the whole spectrum of communities by applying first our method to detect large and medium size communities, then, on the residual graph, the Trawling algorithm to find the smaller communities left. The efficiency of the Trawling algorithm is likely to be boosted by its application to a residual graph purified of larger communities that tend to be re-discovered several times. We plan the coupling of our heuristic with the Trawling algorithm as future work. One open problem is that of devising an efficient version the ExtractCommunity in the data stream model in order to cope with instances of the web-graph stored in secondary memory.

Web 2001 - 5686 communities found at t=10													
# Centers	≥ 100	92	21	49	24	5	8	7	2	8	6	1	11
	[50, 100[185	35	48	38	11	26	9	7	16	11	9	22
	[25, 50[247	54	136	52	28	89	17	6	52	13	14	100
	[10, 25[167	68	437	13	29	217	1	20	163	17	23	347
		low	med	high	low	med	high	low	med	high	low	med	high
		Density			Density			Density			Density		
		[10, 25[[25, 50[[50, 100[≥ 100		
		# of Fans											
Italy 2004 - 1099 communities found at t=10													
# Centers	≥ 100	17	3	11	3	1	5	2	2	0	2	1	12
	[50, 100[32	2	14	14	2	4	5	1	2	3	4	15
	[25, 50[28	15	33	10	2	18	5	7	16	19	11	69
	[10, 25[14	5	42	1	3	26	1	2	34	5	11	247
		low	med	high	low	med	high	low	med	high	low	med	high
		Density			Density			Density			Density		
		[10, 25[[25, 50[[50, 100[≥ 100		
		# of Fans											
United Kingdom 2005 - 4220 communities found at t=10													
# Centers	≥ 100	24	5	18	17	4	15	10	3	14	11	5	51
	[50, 100[63	23	55	14	21	34	19	11	42	24	22	81
	[25, 50[76	23	151	28	18	159	16	7	68	51	22	273
	[10, 25[43	30	299	7	8	266	8	11	159	34	44	705
		low	med	high	low	med	high	low	med	high	low	med	high
		Density			Density			Density			Density		
		[10, 25[[25, 50[[50, 100[≥ 100		
		# of Fans											

Table 6: Distribution of the detected communities depending on number of fans, centers, and density, for $t = 10$.

Thresh.	Web 2001			Italy 2004			Uk 2005		
	# Total	# in Com.	Perc.	# Total	# in Com.	Perc.	# Total	# in Com.	Perc.
10	984 290	581 828	59%	3 331 358	3 031 723	91%	4 085 309	3 744 159	92%
15	550 206	286 629	52%	2 225 414	2 009 107	90%	3 476 321	3 172 338	91%
20	354 971	164 501	46%	1 761 160	642 960	37%	2 923 794	2 752 726	94%
25	244 751	105 500	43%	487 866	284 218	58%	2 652 204	2 503 226	94%

Table 7: Coverage of communities found in the web graphs. The leftmost column shows the threshold value. For each data set, the first column is the number of pages with $d^+ > t$, and the second and third columns are the number and percentage of pages that have been found to be a fan of some community.

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Cl. ID	Cl. Keywords	# Comm.	# Rel. Comm.	Prevalent Type
1	poker (0.66) casino (1.0) games (0.80)	(8)	8	- gambling
2	phone (0.71) nokia (1.0) motorola (0.31)	(17)	17	- mobile phones
10	men (0.15) lingerie (0.16) women (0.23)	(14)	14	- clothing/underware
14	antique (1.0) auction (0.11) search (0.19)	(5)	4	- antiques
22	car (1.0) hire (0.29) cheap (0.13)	(25)	20	- car sales/rent
25	hotel (0.65) holiday (1.0) travel (0.22)	(36)	34	- tourism/travel
27	delivery (0.31) flowers (1.0) gifts (0.66)	(8)	8	- gifts and flowers
31	credit (0.54) loans (1.0) insurance (0.56)	(36)	28	- financial services
32	city (0.59) council (1.0) community (0.31)	(7)	6	- city councils

Table 8: Some notable clusters of communities in the data set UK05 for $t = 25$. Parameters used for filtering and clustering: # fans=0-1000, # centers=10-max, average degree =10-max, target=70 clusters (55 done). Communities in the filtered data set: 636. We report, for each cluster, id number, keywords with weights, number of communities in the cluster and how many of these are relevant to the prevalent type.

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