Dependence Communities in Software

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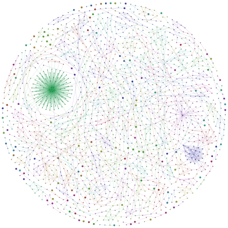
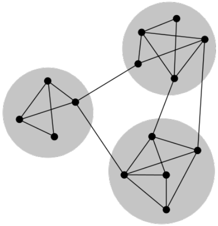


Communities in Graphs

A network is said to have *community structure* if the nodes of the network can be easily grouped into (potentially overlapping) sets of nodes such that each set of nodes is densely connected internally, with few connections to the rest of the network.



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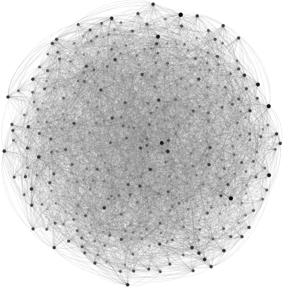
Not all networks have community structure e.g. random graphs



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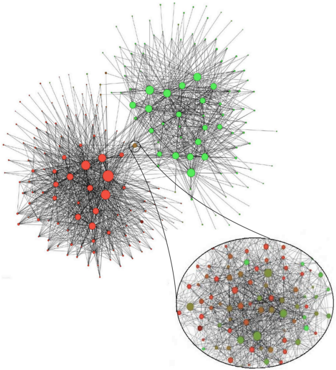

“Graphical representation of the network of communities extracted from a Belgian mobile phone network. About 2M customers are represented on this network. The size of a node is proportional to the number of individuals in the corresponding community and its colour on a red-green scale represents the main language spoken in the community (red for French and green for Dutch). Only the communities composed of more than 100 customers have been plotted. Notice the intermediate community of mixed colours between the two main language clusters. A zoom at higher resolution reveals that it is made of several sub-communities with less apparent language separation.”

(Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks.

Journal of Statistical Mechanics: Theory and Experiment, 2008(10), P10008. doi:10.1088/1742-5468/2008/10/P10008)

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Previous work has shown community structure exists in class dependence graphs.

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Finally we see if these communities reflect anything semantic.

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Perhaps dependence communities will highlight different semantic concerns within a program.

Modularity

Given a partition of a network, modularity is a measure of the 'strength' of the community structure of this partition.

$$Q = \begin{array}{c}\text{(fraction of edges that fall}\\ \text{within communities in the}\\ \text{given graph)}\end{array} - \begin{array}{c}\text{(expected number of edges}\\ \text{within those communities}\\ \text{in the null model)}\end{array} \tag{1}$$

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Modularity, of a weighted undirected graph, is defined as

$$Q = \frac{1}{2m}\sum_{i,j}\left[A_{ij} - E_{ij}\right]\delta(c_i, c_j) \qquad (2)$$

where A_{ij} is the weight of the edge incident to i and j, $k_i = \sum_j A_{ij}$ is the sum of the weights of the edges incident to vertex i, c_i is the community to which vertex i is assigned, $\delta(u, v)$ is 1 if i and j are in the same community and 0 otherwise and $m = \frac{1}{2}\sum_{i,j} A_{ij}$. E_{ij} is the expected number of edges between i and j in a random graph of the same degree distribution which can be calculated as $\frac{k_i k_j}{2m}$.

Algorithms for Finding Comunities

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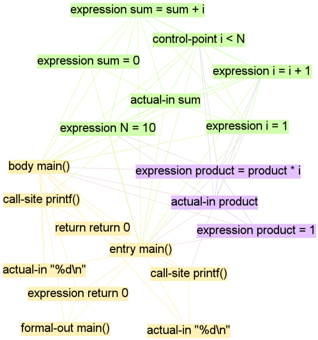
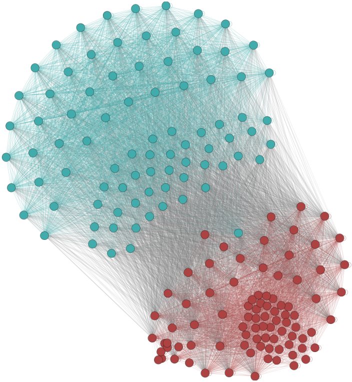
This technique is simple, fast and has good accuracy and has been tested on networks with millions of vertices/edges.

Example of Communities in the Slice Graph: Sum/Product

```
int main() {

        const int N = 10;
        int sum = 0;
        int product = 1;
        int i = 1;

        while(i < N) {
           sum = sum + i;
           product = product * i;
           i = i + 1;
        }

        printf("%d\n", sum);
        printf("%d\n", product);
}
```



Example of Communities in the Slice Graph: Word Count Program



It separates out the code that does the counting from the code that does the I/O.

More Examples of Communities in the Slice Graph

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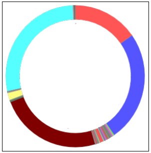

GNU Chess: frontend, adapter and engine

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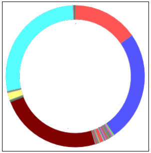

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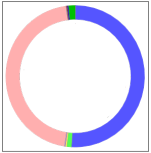

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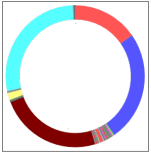

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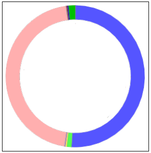

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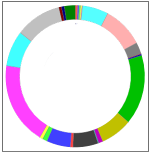
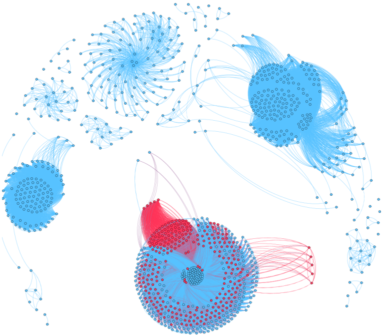


GNU robots: many communities due to low coupling

Applications - Detecting Dynamic Watermarks in Java Code



The red bits are the dynamic watermark we injected.

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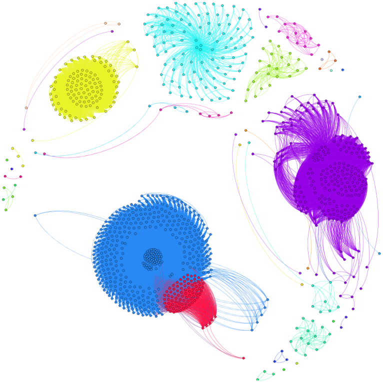

The red bits are the bits of the watermark discovered by the communites algorithm.

Dependence Clusters vs. Dependence Communities

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Perhaps Dependence Communites are a 'good enough' approximation for what is required for Dependence Clusters.

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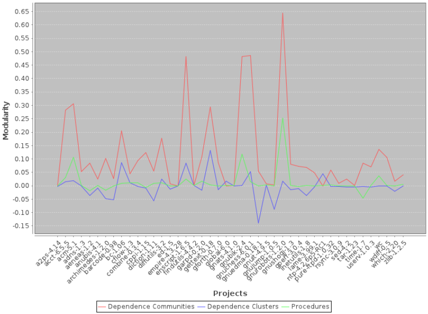
It turns out that, If we apply the Louvain algorithm to the same graphs we get a partition with higher modularity. In other words it produces ‘clusters’ with a stronger ‘internal inter-dependence’ than those produced by Harman’s approximation.



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. . . or at least a better approximation to the properties of programs that authors are trying to capture using Dependence Clusters!

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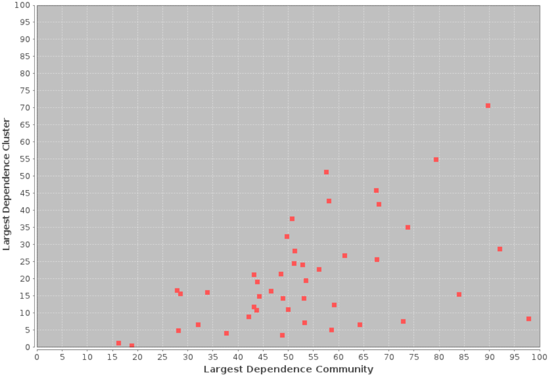

$$R = 0.8, p < 0.00001$$

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Dependence Communities reflect semantic properties of a program.

Thanks

Thanks for listening.

Any questions?