Software Clusterings with Vector Semantics and the Call Graph

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- When there is no specific definition of it, we can attempt to recover it
- One particular problem is the **clustering of its components into modules**
- Many methods exist in literature

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1. Provide a method for software clusterings through **vector semantics** and the **call graph**
2. Evaluate our method on the **Linux Kernel Codebase**
3. Compare it against state-of-the-art methods (ACDC [12], LIMBO [1]) and agglomerative clustering methods (agglomerative clustering [9, 4, 13])

Our approach I

We took a simple approach to the problem

1. Define the initial "grains" of the system. With the term "grains" we can refer e.g. to source files (.c), source (.c) and header (.h) files (combined) as well as one-top directory modules.
2. Preprocess the files attributed to the "grains"
3. Train a Skip-Gram model (Doc2Vec [6]) on them and obtain vector representations of the "grains" $\mathbf{x}_1, \dots, \mathbf{x}_n$
4. Generate the call graphs of the system using a static code analyzer (e.g. CScout [10])

Our approach II

5. Put weights on the graph minor $H(V, E)$ induced by the "grains" as the normalized cosine similarities between them

$$w(i,j) = \frac{1 + \cos(\mathbf{x}_i, \mathbf{x}_j)}{2} \qquad \forall (i,j) \in E(H)$$

6. Run Louvain Community Detection on H and obtain software clusterings

Preprocessing

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2. For example `zone_seqlock_init` becomes `zone`, `seqlock`, `init` and `inprogress` becomes `in` and `progress`
3. The resulting tokens are lemmatized using the English Lemmatizer provided by the spaCy [5] package

Embeddings

A Skip-Gram model is trained. The objective of such a model is to maximize the probability that a word appears in a window (context) of size $2k + 1$

$$\frac{1}{N} \sum_{t=k}^{N-k} \log \Pr[w_t \mid w_{t-k}, \ldots, w_{t+k}]$$

where

$$\Pr[w_c \mid w_t] = \frac{\exp(s(w_c, w_t))}{\sum_{j=1}^{V} \exp(s(w_t, j))}$$

We have used Doc2Vec for our training which extends the aforementioned idea to extract document embeddings.

The Linux Kernel Codebase

- A **HUGE** codebase consisting of ∼20.3 million lines of source code

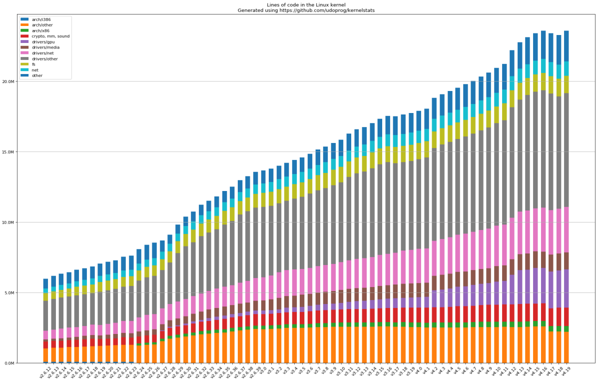

Figure: Linux Kernel Codebase Size over time. Source: Reddit

- Constantly growing
- Easy-to-find ground truth for evaluation

Call Graphs I

The call graphs were extracted with CScout [10] and are of the following forms

1. Macro and Function Call Graph
2. Control Dependency Graph
3. File include Graph
4. Compile-time Dependency Graph
5. Data dependency Graph (through globals)

The extraction of the call graphs took $\sim$ 10h and required $\sim$ 32GB of RAM on a Debian server.

Call Graphs II

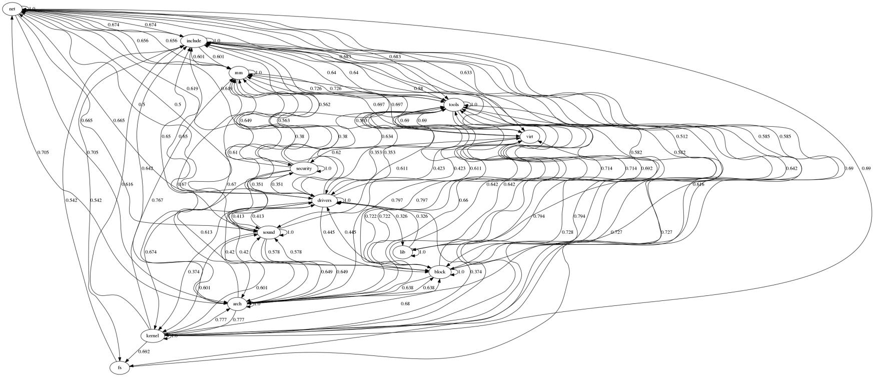

Figure: Call Graph Example between Kernel one-level directories

Preparing the graph for clustering

- The weights assigned to every edge are the normalized cosine similarities

$$\cos(\mathbf{x}_i, \mathbf{x}_j) = \frac{\langle \mathbf{x}_i, \mathbf{x}_j \rangle}{\|\mathbf{x}_i\| \|\mathbf{x}_j\|}$$

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- Experiments were run using both the directed and the undirected version of the graph. The directed version of the graph required doing a bipartite transformation [7] where every edge (i,j) was mapped to $\{i, j'\}$ where j' was a copy of $j \in V$. After community detection, the communities which j and j' belonged to were merged using a union-find data structure.

Louvain Community Detection I

- The Louvain method for community detection aims to produce communities which maximize the modularity function

$$Q(H) = \frac{1}{2m} \sum_{(i,j) \in E(H)} \left(w(i,j) - \frac{k(i)k(j)}{2m} \right)$$

where $m = \sum_{(i,j) \in E} w(i,j)$ and $k(i) = \sum_{j \in \mathrm{in}(i)} w(i,j)$.

Louvain Community Detection II

- The change $\Delta Q(i,j)$ in modularity is derived as

$$\Delta Q = \left[\frac{\Sigma_{in} + 2k_{in}(i)}{2m} - \left(\frac{\Sigma_{tot} + k(i)}{2m}\right)^2\right] - \left[\frac{\Sigma_{in}}{2m} - \left(\frac{\Sigma_{tot}}{2m}\right)^2 - \left(\frac{k(i)}{2m}\right)^2\right]$$

  where Σ_{in} is sum of all the weights of the links inside the community i is moving into, Σ_{tot} is the sum of all the weights of the links to nodes in the community i is moving into, $k_{in}(i)$ is the sum of the weights of the links between i and other nodes in the community that i is moving into.
- The communities that Louvain Clustering produces

The MoJo Clustering Distance

The MoJo [11] metric is a clustering distance metric used for comparing software clusterings. The MoJo distance between two clusterings $\mathcal{C}_1, \mathcal{C}_2$ is defined as the minimum number of moves and joins to transform one clustering to another where

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$$\mathrm{MoJo}(\mathcal{C}_1, \mathcal{C}_2) = \mathsf{min}\{\mathrm{mno}(\mathcal{C}_1, \mathcal{C}_2), \mathrm{mno}(\mathcal{C}_2, \mathcal{C}_1)\}$$

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- Exact computation is not **efficient** so a **heuristic** is proposed.

Agglomerative Clustering I

Idea

In every iteration pick two points/vertices u and v that maximize a linkage function and merge them together.

Algorithm

function $\textsc{AgglomerativeClustering}(w, L, m, \mathbf{x}_1, \dots, \mathbf{x}_n)$
  $\mathcal{C}_0 \leftarrow \{\{\mathbf{x}_1,\}, \dots, \{\mathbf{x}_n\}\}$
  for $1 \le t \le m$ **do**
    $(\hat{A}, \hat{B}) \leftarrow \operatorname{argmax}_{A,B \in \mathcal{C}_{t-1}} L(|A|, |B|, w(A, B))$
    $\mathcal{C}_t \leftarrow \mathcal{C}_{t-1} \setminus \{\{\hat{A}\}, \{\hat{B}\}\} \cup \{\{\hat{A} \cup \hat{B}\}\}$
  end for
  return $\mathcal{C}_m$
end function

Agglomerative Clustering II

Linkage functions vary

- Average Linkage[1] $\mathrm{argmax}_{A,B} \frac{w(A,B)}{|A||B|}$
- Complete Linkage $\mathrm{argmax}_{a \in A, b \in B} w(a,b)$
- Single Linkage $\mathrm{argmin}_{a \in A, b \in B} w(a,b)$
- Ward Linkage
- Information Loss (Agglomerative Information Bottleneck Algorithm)

The affinity function w can be any distance measure. In our comparison, we have used the cosine distance affinity measure between the document embeddings.

[1] $w(A,B) = \sum_{a \in A, b \in B} w(a,b)$

Main Software Clustering Algorithms

The two main algorithms appearing in literature [8, 2] are

- LIMBO
- ACDC

Evaluation

- Our method was tested on Linux 4.21, consisting of 20.3 million SLOC against Average-Linkage [9], Complete-Linkage [4] and Ward-Linkage [13] using the same document embeddings as well as ACDC with structural information [12] and LIMBO [1] with Bag-of-Words features.
- As ground truth, we have used the first level directories as a target clustering and as input, we have considered the modules of the one-top directories.
- For example, the source code file `drivers/net/ieee802154/mcr20a.c` has a ground truth value of `drivers` and it is considered under the same module as every `.c` and `.h` file under `drivers/net/ieee802154`.
- Results are averaged over runs

Results

Alg.	Dim.	n_c	Range	$\bar{x}$	σ	Median	Dist.
ACDC	–	9055	1 – 4245	5	46	2	33694
Average Linkage	*300*	*21*	1–3406	163	725	1	2092
Complete Linkage	*300*	*21*	1–1529	163	412	19	1710
LIMBO [2]	12317	*21*	50–1810	163	375	50	1482
Ward Linkage[3]	*300*	*21*	21–948	163	223	70	1138
SADE	*300*	10 ($\pm$ 2)	2 ($\pm$ 0) -132 ($\pm$ 13)	64 ($\pm$ 4)	40 ($\pm$ 4)	65 ($\pm$ 10)	243 ($\pm$ 1)
SADE (Directed)	*300*	5 ($\pm$ 2)	1 ($\pm$ 1) - 614 ($\pm$ 1)	141 ($\pm$ 39)	253 ($\pm$ 25)	2 ($\pm$ 0.3)	237 ($\pm$ 2)
Ground Truth	–	21	1–1348	163	341	11.0	–

Table: Experimental Results for Linux 4.21. Italics denote manually defined parameters

[2] $(B = 100,\ S = \infty)$
[3] Eucledian Affinity

Results & Discussion

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- Surpass all clustering algorithms in terms of MoJo Distance Metric
- Production of balanced clusterings
- Production of stable clusterings
- Results were produced without knowing the number of clusters of the ground truth a priori
- Provide a simplistic approach to software clustering combining vector semantics and the call graph

Conclusions

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2. Performing our study on a very large system (Linux) gives us further insight on the nature of software itself
3. Outperform state-of-the-art and baseline methods in terms of **authoritativeness** and **extremity**
4. Produce **stable** and **balanced** clusterings

Future Work

- Development of evaluation policies with users should be taken into account, especially when dealing with old codebases lacking technical documentation.
- Integration with more static analyzers

Code and Data

Refererences

SourceCode

Paper

`https://github.com/papachristoumarios/sade`

Dataset

Thank you!

`https://github.com/papachristoumarios/sade`

`https://zenodo.org/record/2652487`

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