On Analyzing the Topology of Commit Histories in Decentralized Version Control Systems

Marco Biazzini
INRIA — Bretagne Atlantique
marco.biazzini@inria.fr

Martin Monperrus
Université de Lille
martin.monperrus@univ–lille1.fr

Benoit Baudry
INRIA — Bretagne Atlantique
benoit.baudry@inria.fr

Abstract—**Empirical analysis of software repositories usually deals with linear histories derived from centralized versioning systems. Decentralized version control systems allow a much richer structure of commit histories, which presents features that are typical of complex graph models. In this paper we bring some evidences of how the very structure of these commit histories carries relevant information about the distributed development process. By means of a novel data structure that we formally define, we analyze the topological characteristics of commit graphs of a sample of GIT projects. Our findings point out the existence of common recurrent structural patterns which identically occur in different projects and can be consider building blocks of distributed collaborative development.**

I. Introduction

Centralized version control systems (CVCS) such as CVS or SVN have a rather sequential history. There is a linear history of committed change sets (or commits), stored on a central server. Branching makes up for some parallelism, but its capability to improve successful collaboration has been thoroughly questioned [1].

On the contrary, the history of Decentralized Version Control Systems (DVCSs) such as Mercurial or GIT is much richer. In decentralized version control systems, each developer has the full commit history of the codebase locally available. This allows for a much more flexible way to handle different concurrent branches. The extreme ease of branch manipulation and combination results in software histories that are much more complex than what is typically found in a traditional centralized systems software.

Bird and colleagues have shown that the analysis of DVCS presents several issues for traditional repository mining techniques and metrics [2], In DVCSs, there are concurrent branches that start from a common ancestor, run in parallel, split, merge together or with other branches, then are finally merged in a commit which gives a "current stable version" of the software product. Such a canopy of development lines demands to redefine concepts such as "developer collaboration", "current state of the code", "amount of contribution", which are fairly easy to establish for CVCSs.

In this paper, we propose to use graph concepts and metrics to characterize DVCSs such as GIT. We consider commit histories of DVCSs as directed acyclic graphs (DAGs) and talk about software development using a general graph characterization (topology, patterns, metrics, etc.). The structure of commit history DAGs is given by the way developers use branches. Their topology reflects the way the software is modified, improved, fixed, in one word, evolved.

Thus there is information hidden in the very structure of the commit history graph, which is relevant to understand key characteristics of the development process typical of DVCSs. In this paper we show that the topology of commit graphs presents recognizable patterns, whose recurrence is due to the nature of the underlying development process itself. Such patterns are not purposely designed by developers, who rather pursuit goals related to the state of their codebase. They thus *emerge* from the topologically rich structure of DVCSs and characterize the way the codebase evolves over time.

To sum up, this paper makes the following contributions:

– The definition of a novel data structure, the repository *Metagraph*, that captures all the relevant information about the DVCSs repositories.

– A classification of the elements of a DVCS commit history, based on their topological relevance in their history graph.

– An analysis of topological properties of the commit history of several open source GIT–based project repositories.

We thus propose a novel way to analyze DVCS–based software project and discuss the evidences that signal its potential in leading to novel insights about the process of collaborative development.

The rest of the paper is organized as follows. Section II presents and formally defines our contribution. Section III describes the settings of our experiments. Section IV discusses our findings and motivates their relevance. Section V presents related work and Section VI draws our conclusion.

II. Topological Analysis of Commit Graphs

The commit history of a decentralized repository can be modeled by a directed acyclic graph whose nodes are commits and edges are parent/child relations between them.

As the history of a project evolves, parallel branches are created and joined in a distributed process of incremental manipulation of the code base. In general (as backed up by statistics we present in the following), the majority of commits belongs to single branches, while fewer are those where the creation or the join of the branches themselves occur.

For the purpose of understanding the global structure of the commit history, i.e. the topology of the commit graph, these latter commits are much more relevant than the former.
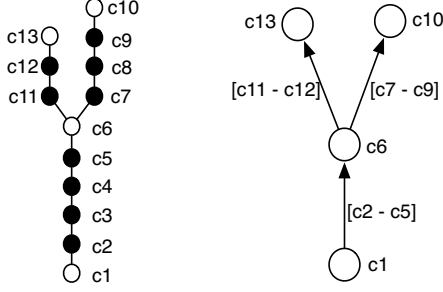
Fig. 1. Example of commit history to *Metagraph* transformation

We propose to classify, from the standpoint of their topological interest, the commits populating a history graph as follows:

– **Terminal**. Commits having no parent or no child.

– **Sequential**. Commits having exactly one parent and one child.

– **Structural**. Non-terminal commits whose union set of parents and children has more than 2 elements.

These categories are devised so that (i) they capture the whole set of commits in a GIT history and (ii) a given commit can belong to one and only one of them. To bridge these definitions with the standard GIT terminology, terminal commits are either first commits or HEADs; sequential commits are non-merging and non-branching ones, excluding first commits and HEADs; structural commits are merging and/or branching commits, which are not HEADs.

Terminal commits are thus the boundaries of the graph, while structural commits are the nodes which define its structure. Sequential commits do not play any role in determining the topology of the graph, being just enqueued in development lines (the branches) which lead from a merge (or branch) commit to another.

Sequential commits are clearly important from the standpoint of the developer contribution to the codebase. They should anyway be bypassed, when analyzing how branches feed each other and the parallel development gets organized in the repository, in order to get rid of topologically irrelevant information, which would bias any metrics.

Thus, a way must be devised to meet conflicting goals:

• Avoiding the overhead and the information noise of sequential commits while analyzing the topology of a commit history graph, in order to be able to obtain meaningful results

• Saving the information about the developer contributions that the sequential commits incorporate, along with their position in the commit history, in order to be able to relate the results of the topological analysis with those derived by other kinds of data mining, which focus on code metrics or process metrics.

We define in the following a data structure and a set of properties that allow to positively solve both issues.

TABLE I.   THE GIT REPOSITORIES UNDER STUDY — PART I.
THE COLUMNS REPORT THE PROJECT'S NAME, THE NUMBER OF COMMITS,
THE NUMBER OF EDGES AND NODES OF ITS *Metagraph*.

Project	commits	edges	nodes
OpenLeague	43	36	25
BroadleafCommerce	4722	784	496
Fridgemagnet	67	12	10
AutoSave	124	15	12
OryzoneBoilerplateBundle	60	20	14
ketama	18	10	7
Edaha	185	11	9
Tolmey	61	29	21
Ai_Class_Octave_Functions	23	13	10
WPide	152	24	17
sexpistol	37	14	10
ace	3220	1139	693
contracted	72	10	8
gitpython	163	37	25
tcesp	81	25	18
bempp	1530	375	246
FReD	211	45	31
testlol	77	12	9
configs	40	18	14
pool	42	14	10
q4wine	966	81	54
pylibemu	59	10	8
sarah	312	19	14
ConcurrenTree	632	91	59
ProWiC	61	30	22
java	95	47	33
flour	209	45	29
Telephus	272	65	43
arkilloid	177	40	27
RLLVMCompile	87	20	15
pants	643	57	40
pelm	415	103	68
jump	49	32	23
a4a	206	68	46
PySynergy	278	23	16
caveman	211	19	14
cocoagit	756	86	57
stsh	239	37	26
zap	28	10	7
iamhanchang	600	202	123
Locke	29	10	8
ConfigServiceProvider	43	16	12
Twittia	86	14	11
MiniCart	124	15	11

A. The Repository Metagraph

We define an original data structure, based on this classification of GIT commits. This structure, called *Metagraph*, encompasses a commit history, focusing on the topologically relevant commits. The *Metagraph* retains all the information from in the commit history. It aims at simplifying structural analyses performed on the repository commit logs of a GIT repository.

Def. — Metagraph
A *Metagraph* Mg of a commit history graph $G = \langle V, E \rangle$ is a multi–graph $Mg = \langle Ve, Me \rangle$, where Ve is the set of nodes which correspond to terminal and structural commits in V and Me is a set of *metaedges* (see next definition). We call *root* the node in Ve associated to the first commit of G.

Def. — metaedge
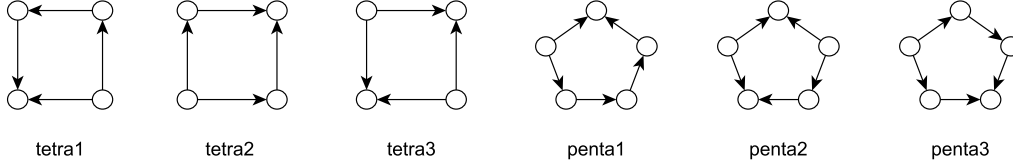Given a *Metagraph* Mg of a commit history graph G, a *metaedge* is a directed edge between commits in the set of

Fig. 2.   Patterns of size 4 and 5.

nodes Ve of Mg.

A *metaedge* me between two nodes Ve_1 and Ve_2 exists in Mg if and only if a path in G exists between the corresponding nodes V_1 and V_2, which is composed uniquely by sequential commits. The list of (sequential) commits composing this path in V is associated (as metadata) to the *metaedge*.

We call Ve_1 (resp. Ve_2) first (resp. last) node of me.

TABLE II.   THE GIT REPOSITORIES UNDER STUDY — PART II.
THE COLUMNS REPORT THE PROJECT'S NAME, THE NUMBER OF COMMITS,
THE NUMBER OF EDGES AND NODES OF ITS *Metagraph*.

Project	commits	edges	nodes
nmrglue	132	12	9
vimclojure	346	18	13
robut	167	58	38
chrome_collector	74	43	29
satellite	161	15	11
PJsonCouch	25	10	8
mailchimp	50	15	11
gtalkjsonproxy	60	10	8
owper	140	15	12
mxn	507	201	121
crab	50	12	11
CRIOJO	273	84	57
n2n	203	75	51
migen	486	15	11
pinocchio	18	13	10
gokogiri	566	124	88
zamboni	13800	1334	865
MailCore	279	69	44
pod	149	20	15
jquery_add_more	32	23	15
blur	997	118	78
hsnews	89	16	11
easyXDM	761	176	116
spidr	635	10	8
pyrocms	14228	7176	4187
statsd	142	62	38
spark	198	21	15
ri_cal	322	18	14
asset_sync	301	109	70
bamboo	55	10	8
perl5i	792	256	164
andthekitchensink	176	18	14
connect	2515	650	410
eksamensnotater	136	65	42
MvvmCrossConference	92	10	8
Newscoop	10721	3742	2208
xyzcmd	594	18	13
tradinggame	69	25	17
CMSC858E	65	34	23
tinycon	53	32	21
cloakstream	56	23	17
iTetrinet	981	167	112
Tir	146	25	17

Figure 1 illustrates a *Metagraph* (right) built from a commit history graph (left). Our definition of *metaedges* serves two main purposes: (i) it simplifies the topology of a commit history by excluding sequential commits from its structure, while preserving the information they carry and (ii) it makes the *Metagraph* a model that focuses on parallel development events (occurrences of branching or merging in the commit history graph G).

Our analysis of *Metagraphs* extracted from GIT repositories is based on the following properties:

Def. *— Metagraph's layer*
For any $v_i \in Ve$, let $dist(v_i) : Ve \to \mathbb{N}$ be a function that maps each node of Mg to its maximum distance from the root of Mg, measured in number of *metaedges*.
A layer L_n in a *Metagraph* Me is defined as
$L_n \subseteq Ve \in Me : l_i \in L_n \iff dist(l_i) = n$.

Layer L_n is thus the set of all nodes having the same maximum distance n from the root. We call n the *index* of the layer. By construction, roots are the only nodes belonging to L_0.

Supposing the example in Figure 1 represents a complete *Metagraph*, we have $L_0 = c1$, $L_1 = c6$ and $L_2 = c10, c13$. The set of layers of a *Metagraph* is a convenient partitioning of its nodes, which groups commits according to their distance from the first commit, measured in terms of number of parallel development events, as captured by the *metaedges*.

Def. *— Width of a layer.*
The width of a layer L_n is equal to its cardinality $|L_n|$.

Def. *— Density of a layer.*
We call density of a layer L_n the number of *metaedges* whose last node is in $L_m, m \geq n$.

The density of a layer L_n is thus the number of *metaedges* terminating either in L_n or in a layer which is farther from the root. By definition, the density of $L_0 = 0$.

Let c_n be a cut of Mg partitioning its nodes in two sets: $Ve_1 = v_i : dist(v_i) < n$ and $Ve_2 = v_j : dist(v_j) \geq n$. Then, the density of L_n is the number of *metaedges* crossing c_n.

Def. *— Diameter of a Metagraph.*
The diameter of a *Metagraph* is equal to the length of the longest path in the *Metagraph*. By construction, it is equal to the greatest layer index of the *Metagraph*.

B. Development Patterns

Since the *Metagraph* captures the structural properties of a commit graph, we now look for evidence of the presence (or

lack thereof) of recurrent development patterns in repository metagraphs.

A way to spot such patterns is to find recurring subgraphs in a *Metagraph* over different projects. Since any subgraph of a *Metagraph* can only be composed by merging and/or branching commits of the project history, the fact that the same subgraph occurs several times in a project *Metagraph* would denote the emergence of the same collaborative pattern at different moments of the project history.

Moreover, the fact that the same subgraph repeatedly occurs in *Metagraphs* which model the history of different projects would point out *emergent patterns* characterizing collaborative development itself, rather than the collaboration habits of a specific community of developers.

The problem of finding all isomorphic subgraphs of a given graph is in general *NP-complete* [3]. Even limiting the size of the subgraphs to target, the feasibility of such a task heavily depends on the structural complexity of the *Metagraph*. Several efficient algorithms exist, though, to find single subgraphs within larger graphs. By restricting the number of targets and narrow down the search to each one of them, we can find all occurrences of specific patterns of a given size (number of nodes).

A way to choose target patterns is needed. We are interested in enlightening the very structure of the *Metagraphs*. Terminal nodes are the ever-changing boundaries of the *Metagraphs* and thus not really relevant for our purposes. We can focus on structural nodes and on the *metaedges* that start from or arrive to structural nodes.

Let us therefore consider the subgraph $Sg = \langle Vs, Ms \rangle$ of a *Metagraph* Mg, composed by the set Vs of all structural nodes of Mg, along with the set Ms of all *metaedges* of Mg whose first and last nodes are both in Vs. Recalling that, by construction, any *metaedge* in Ms must either start form or end to a node in Vs, it is easy to see that all subgraphs of Sg are either isomorphic to simple polygons or to polygons composed by adjacent polygons of smaller size. Figure 3 exemplifies our point by showing two isomorphic graphs.

Thus the quest for patterns becomes the search for all polygon subgraphs in Sg. Finding simple polygons is enough, because it is easy to spot out composed polygons, by tracking common nodes among simple (smaller) polygons. Such a task is accomplished by finding induced subgraphs in Mg, which are isomorphic to simple polygons.

We thus propose the following definition.

Def. — *Pattern*
We call pattern any induced subgraph of a *Metagraph*, which is isomorphic to a polygon graph.

As *metaedges* are always directed, there are several different (*i.e.*, non–isomorphic) patterns of any given size $s, s > 3$. Thus the relevance of a pattern may not be given only by its size, but also by its very topology. Since we are interested in characterizing the way collaborative development shapes commit histories, we propose a simple way to discriminate between patterns of *incremental development* and patterns of *code integration*. Clearly both aspects are always present in any

pattern, but their relative relevance may differ, as we exemplify in the following.
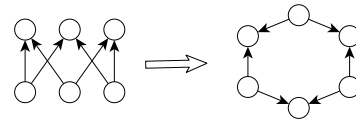

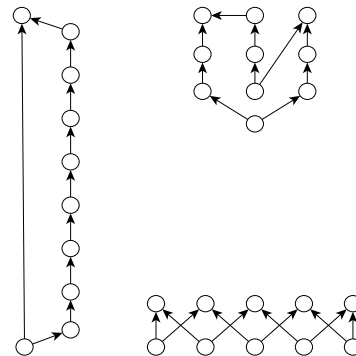Fig. 3.   Isomorphic simple acyclic digraphs of degree 2.

Fig. 4.   Patterns of size 10 showing a different slenderness.

Being our patterns simple acyclic digraphs of degree 2, each pattern is composed of two or more walks. The lengths of these walks fall in the interval $]0, 1, \ldots, N[$, where N is the size of the pattern. Considering the topology of a pattern, the presence (resp. absence) of few longer walks indicates a greater (resp. smaller) relevance of incremental developing w.r.t. code integration. Figure 4 intuitively shows how three identically sized patterns can be different from this standpoint.

In order to classify patterns of different size w.r.t. the kind of collaboration they entail, and, more generally, to compare them w.r.t. this criterion, we propose to compute their *slenderness*, defined as follows:

Def. — *Pattern's slenderness*
The slenderness of a pattern is a real number in $[0 \ldots 1[$, computed as the number of vertexes that are internal to its walks, divided by the size of the pattern.

Intuitively, a higher (resp. lower) slenderness denotes a pattern where incremental development (resp. code integration) dominates over its counterpart. For instance, the patterns in Figure 4 have a slenderness of $8/10 = 0.8$ (left), $6/10 = 0.6$ (top right) and $0/10 = 0$ (bottom right), which well denotes the fact that the first pattern is strongly incremental, while the second balance increments and integration (with a slight dominance of the first) and the third pattern is all about integration.

The results presented in the following show that recurring patterns indeed characterize commit histories of a sample of GIT–based projects.

We underline that such patterns would not be detectable on "raw" commit history graphs, because sequential commits

Name	Size	How many
tri	3	1
tetra*	4	3
penta*	5	3
exa*	6	8
epta*	7	9
octa*	8	20
enna*	9	28
deca*	10	53

"overwhelm" their structure destroying relevant topology properties. Thanks to the transformation to *Metagraphs*, the very structure of commit graphs can be successfully mined from a topological standpoint.

III.   EXPERIMENTAL DESIGN

We present an experiment that aims at identifying development patterns in a sample of GIT repositories, collected from GITHUB. For each repository, we build a *Metagraph* modeling its commit history. We then detect patterns in the topology of the *Metagraphs* and analyze their characteristics.

A. Experimental Data

The experimental data comes from GITHUB, an Internet hosting service for open source software. According to FLOSSmole [4] (Free Libre Open Source Software) statistics, GITHUB had 191765 repositories publicly available in May 2012. In order to obtain a statistically representative sample of GITHUB hosted projects, we order these projects according to the number of watchers. To discard outliers and less significant entries, we decide to cut off the extrema of the range, *i.e.* projects whose number of watchers is less than 2 or more than 1000. Then we select 1% of the projects in each of three subsets:

- Projects that had from 2 to 9 watchers (total: 30236; sampled: 303)

- Projects that had from 10 to 99 watchers (total: 3554; sampled: 36)

- Projects that had from 100 to 999 watchers (total: 286; sampled: 3)

This way, we obtain a set of 342 GIT repositories. We then discard those having a too poor structure, which we define as less than 10 *metaedges* in their *Metagraph*. We finally obtain a set of 87 projects, listed in Tables I and II.

B. Patterns and Metagraph Properties

As explained above, we define patterns as polygonal induced subgraphs of our *Metagraphs*. We limit our analysis to patterns from size 3 to size 10, because small patterns are trivial and large patterns are too costly to compute. There are 125 non–isomorphic patterns within this size range. For instance, there is only one pattern of size 3, which corresponds to a triangle. Figure 2 shows all patterns of size 4 and 5.

To ease the references to each pattern in the following, we use some arbitrary nicknames, composed by the greek name of numbers from three to ten and by a numerical index. Table III summarizes the information about the "families" of patterns
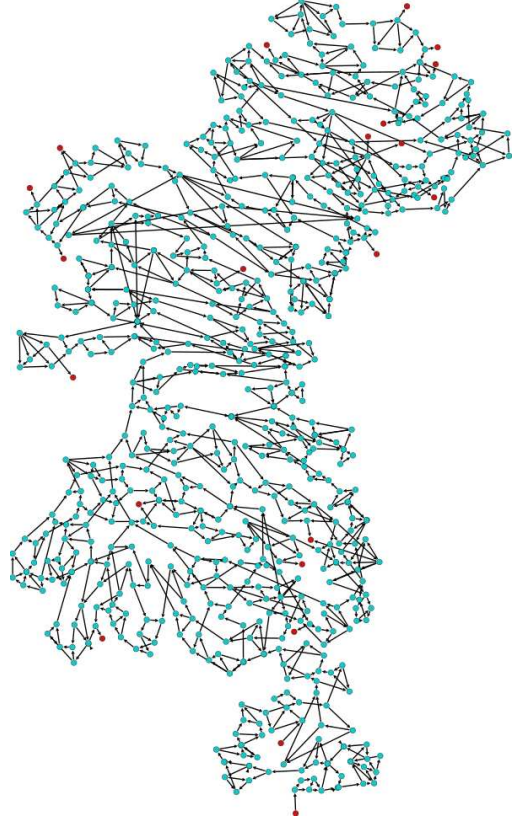

Fig. 5.   *Metagraph* of the `ace` project. Root at the bottom; other red nodes are branches' heads.

we consider. The third column reports the number of existing non–isomorphic instances of each pattern.

It is important to recall that any pattern can only occur in a *Metagraph* of a commit history where two or more parallel lines of development exist, since patterns are composed by structural nodes, which by themselves imply the existence of more than one branch. Thus, whenever a pattern is found in a *Metagraph*, it is implied that those nodes whose in–degree and out–degree is equal to 1 *within* the pattern are actually linked to other nodes of the *Metagraph*, which are not part of the same pattern.

We define two sets of patterns, named *increment* and *integration*. All patterns having a slenderness greater or equal to 0.5 are assigned to the first set, while the others fall into the second.

In the following, we use the expression *category* to refer to any of the families and sets of patterns we just defined.

C. Implementation

In order to perform our analysis, we developed a toolset called GitWorks, as a pure Java application. GitWorks uses JGit[1] to extract information from GIT repositories, then build
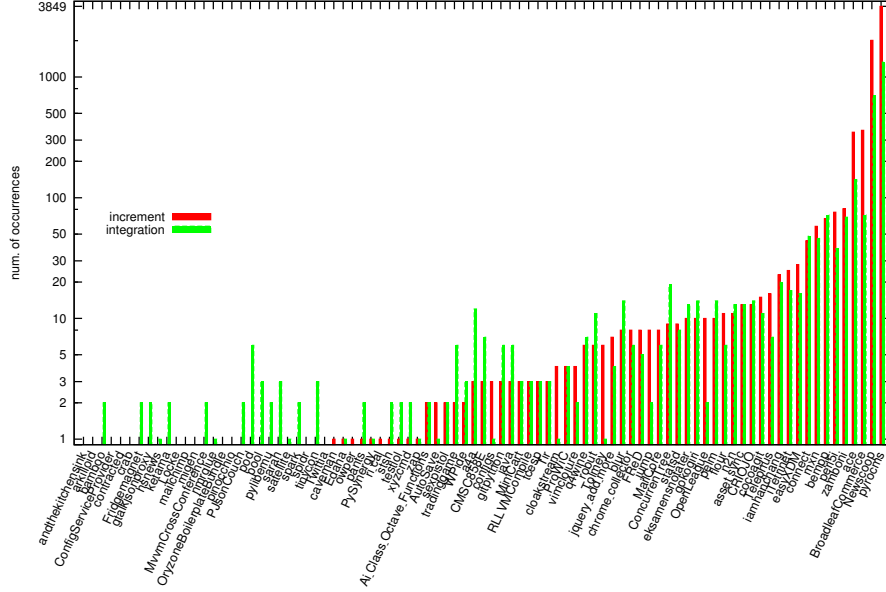
---

[1]http://eclipse.org/jgit/

Fig. 6. Occurrences of increment and integration patterns.

Metagraphs and extract several features from the collected data. GitWorks is freely available on GITHUB[2].

In order to extract the occurrences of patterns in the *Metagraph*, we use the Grochow–Kellis subgraph detection algorithm, based on symmetry breaking [5]. The implementation of the algorithm has been provided by the authors.

To allow the reproduction of our results, input and output data, along with the version of the code we used, are publicly available in a GIT single–branch checkout.[3]

D. Research Questions

R.Q. 1 — Can we find significant recurring structures in DVCS histories?
Our purpose is to see whether there are patterns in commit histories which repeatedly occur. For smaller patterns (*e.g.*, of size 3 and 4), such a phenomenon can be an explicit choice of developers, which implies that such patterns are found useful for their collaborative job. For larger patterns, repeating occurrences can be considered *emergent features* of the topology of the repository. We want to study their relation with the structure of the commit history and with the activity of the developers.

R.Q. 2 — Does the structure of DVCS evolve over time?
If structural patterns can be detected, we want to understand how they change along the history of a project, i.e. whether some collaboration patterns are more frequent at the beginning of a project or in its maturity. This may be relevant for a further analysis of each repository. If a commit history is morphologically characterized by specific patterns at specific

stages of its evolution, it may be worth investigating for information about the way developer collaboration change over time.

R.Q. 3 — Is the occurrence of patterns correlated with increased concurrent development activities?
Whenever patterns appear, they may signal a particular increase of activity in the project. Patterns that tend to appear whenever activity increases or decreases may then be correlated to the strengthening of the project in terms of development or code base.

R.Q. 4 — Are there structural similarities among DVCS histories?
We aim at finding evidences of the existence (or the lack thereof) of same subgraphs in unrelated projects. Such a finding would indicate that there are "universal" patterns of development collaboration. This could then highlight common problems or strong points of different development communities.

IV. EXPERIMENTAL RESULTS

In this section, we present the outcomes of our analysis and discuss their relevance. We first present our results related to the properties of the *Metagraphs* and the detection of patterns. Then we discuss their meaning and propose our answers to the research questions.

A. Metagraph Properties

The *Metagraphs* that model the commit graphs of our sample are indeed quite diverse, from very simple parallel organization to very complex structures. Figure 5 depicts a topologically rich *Metagraph*.

---

[2]https://github.com/marbiaz/GitWorks
[3]`git clone --branch gitworks-icsme14 \`
`--single-branch` https://github.com/DIVERSIFY-project/data

In order to spot relevant characteristics, we analyzed basic *Metagraph* features (listed in Tables I and II) and layer–related properties. Results in Table IV and V have all been found statistically significant, with $p-values << 0.01$.

Table IV shows Pearson's correlation between each couple of *Metagraph* features, plus the number of authors per repository, measured over the whole ensemble of repositories.

TABLE IV. METAGRAPH FEATURES CORRELATIONS.

	nodes	edges	commits
edges	0.99978	—	—
commits	0.86953	0.86000	—
authors	0.91235	0.91190	0.77873

Interestingly, *Metagraph* features are more correlated to the dimension of the developer community (number of authors) than to their total amount of contributions (number of commits).

Metagraph's layers present high variability in terms of time range: from few seconds to hundreds of days elapse between two consecutive layers. We thus measured, in each *Metagraph* the time range spanned by layers and we tested the correlation of their minimum, median and maximum value with the properties of their respective *Metagraphs*, defined in Section II-A.

Table V shows the resulting Spearmans' correlation values.

TABLE V. LAYER PROPERTIES CORRELATIONS. THE SUFFIX *tr* STANDS FOR LAYER'S TIME RANGE.

	diameter	min_{tr}	med_{tr}	max width
min_{tr}	**-0.800941**	—	—	—
med_{tr}	-0.58116	0.41084	—	—
max width	0.54177	-0.424114	n.s.	—
max density	**0.69206**	-0.59806	-0.3154	0.69646

Among the reported values, we see a fairly high correlation between diameter and layer maximum density. It indicates that the two sizes of the *Metagraphs* are positively correlated: the more the layers in a *Metagraphs*, the more they tend to be dense. Thus incremental development and synchronization practices follow a similar trend.

The inverse correlation between diameter and minimum layer time range is also noteworthy. The more the layers, the shorter is the time span they tend to cover

B. Patterns

We first detect, in each repository *Metagraph*, all patterns from size 3 to size 10. Figure 6 shows, for each *Metagraph*, the number of patterns belonging to the increment and integration categories.

The *Metagraphs* are sorted according to the number of increment patterns. It is visible a trend that somehow backs up the correlation values in Table V. Integration patterns tend to be more as the number of increment patterns grows, but the trend seems to be stable only for larger repositories (which happen to be on the right side of the plot).

We also notice that integration patterns are found in smaller repositories where increment patterns are not. This outcome is due to the fact most of pattern of size $s < 5$ fall into the integration category.

In order to investigate if and how the properties of the *Metagraph* are associated with occurrences of patterns, we analyze the relations between patterns and the structural properties of the *Metagraph* (diameter, layer width and density).

Figure 8 shows the occurrences of patterns in one of the largest *Metagraphs* of our sample. The same figure also gives a synopsis of layer densities and widths. All patterns, but `tri` and to some extent `tetra*`, seem to be particularly sensitive to layer properties, thus clustering more where layers are denser.
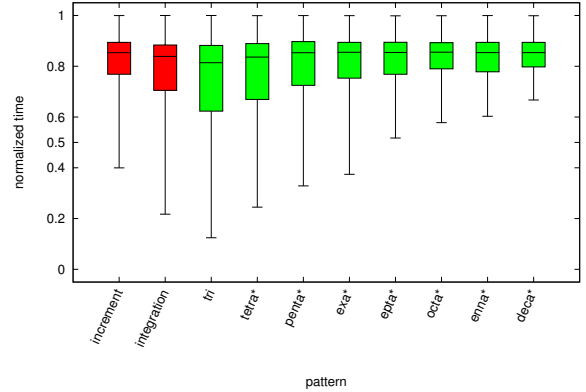

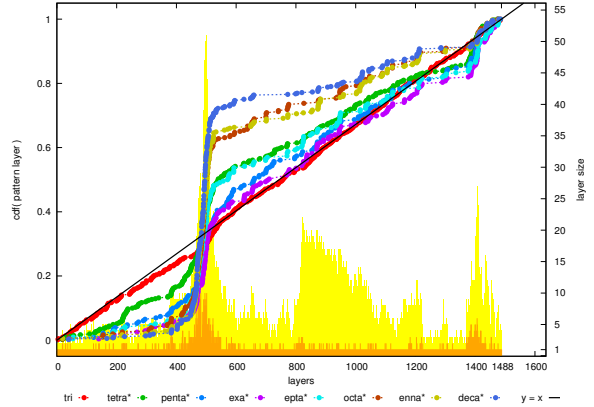Fig. 7. Distribution of timestamps of structural commits per pattern.

Fig. 8. Cumulative distribution of patterns in the Newscoop metagraph. The cdf values of pattern occurrences, grouped per size, are given on the left axis, while the right axis gives the values of the layer width (orange vertical bars) and density (yellow vertical bars). The black line traces the slope of a linearly uniform distribution across the *Metagraph*'s layers.

Patterns occur at different moments of projects histories. Figure 7 shows the distribution of timestamps of *Metagraphs* vertexes belonging to patterns for each category we defined. Data are aggregated over all the *Metagraphs*, thus we normalize the timestamps in the interval $[0..1]$, by simply computing the relative displacement of every commit timestamp w.r.t. the minimum and maximum timestamp in each *Metagraph*. The boxplots are standard interquartile plus whiskers to cover 95% of data points. Outliers are not shown, to improve legibility.

For instance, the boxplot related to the `tetra*` category

shows that, considering the whole ensemble of repository in our sample, these patterns occur anywhere after 10% of the age of a repository is elapsed, half of them is found in the last 20% of repository lifetime (check the position of the median) and they get closer to each other in time as projects grow old (check the different size of the two halves of box and whiskers).

We see how patterns of higher size tend to occur later than smaller ones. The skew towards the top is somehow biased by the fact that we compare project of different age and size, thus, in our case, the normalization of outcomes of smaller project tends to give high values. Nonetheless, it is true that larger patterns are definitely more numerous in the second half of projects' life.

The first two boxplots show that increment patterns tend to occur substantially later than integration pattern.

Table VI presents the results of a comparative analysis of the number of authors and commits among *metaedges* which belong to patterns and which do not. In order to summarize a large amount of data, we present these results as dominance scores of the main aggregates. Each triplet reports the number of projects where a given aggregate (*i.e.*, minimum, median or maximum) measured in a pattern is ⟨less_than–equal_to–greater_than⟩ the same aggregate measured in *metaedges* non belonging to a pattern. For instance, the first case on the left tells that the minimum number of distinct authors in *metaedges* belonging to increment patterns is greater than the minimum of *metaedges* non belonging to any patterns in 40 projects out of 59. Only projects where the considered patterns appear are taken into account, thus the triplets sum up to less than 87.

We see that pattern *metaedges* consistently dominate the others w.r.t. the minimum and the median number of distinct authors, while they usually carry less sequential commits.

TABLE VI.   DOMINANCE COUNTS FOR AUTHORS AND COMMITS IN PATTERNS.

Patterns	Authors			Commits		
	min	med	max	min	med	max
increment	1–18–**40**	10–**33**–16	**34**–19–6	21–**35**–3	**57**–1–1	**56**–1–2
integration	1–24–**46**	7–**34**–30	**41**–20–10	26–**44**–1	**65**–4–2	**63**–2–6
tri	1–24–**46**	9–**33**–29	**40**–19–12	26–**44**–1	**64**–5–2	**63**–2–6
*tetra**	1–16–**38**	9–**30**–16	**31**–18–6	18–**35**–4	**54**–1–0	**53**–0–2
*penta**	0–9–**26**	7–**15**–13	**24**–9–2	9–**26**–0	**32**–2–1	**33**–0–2
*exa**	0–7–**25**	4–**17**–11	**19**–8–5	8–**23**–1	**30**–1–1	**31**–1–0
*epta**	0–5–**16**	2–**11**–8	**15**–4–2	5–**16**–0	**21**–0–0	**21**–0–0
*octa**	0–4–**13**	2–7–**8**	**12**–3–2	4–**13**–0	**16**–1–0	**17**–0–0
*enna**	0–4–**15**	2–6–**11**	**14**–4–1	4–**15**–0	**17**–0–2	**18**–0–1
*deca**	0–2–**13**	2–4–**9**	**12**–2–1	2–**13**–0	**14**–0–1	**15**–0–0

C. Discussion

As said, the definition of *Metagraphs* as models of commit graphs allows a novel kind of topological analysis of repositories.

Several properties of the *Metagraphs* offer interesting standpoints for further analysis of single projects. The results we present aggregate measures of diverse repositories and are not meant to offer a precise description of any of them. They rather point out interesting features which shall be further investigated both at the aggregate level and project by project, in order to reveal their specific importance.

In the following, we discuss our results by recalling and answering our research questions.

R.Q. 1 — Can we find significant recurring structures in DVCS histories?
Answer — The patterns we discover are the very evidence of concurrent development in a GIT repository. As Figure 8 shows, in general patterns, and most of all smaller ones (size 3 to 5), are distributed across *Metagraph* layers. This means that they are not related to a particular "development stage" of the software (which may be identified at given sets of subsequent layers), but rather to the parallel development process itself.

Nonetheless, most patterns are found where the "footprint" of the *Metagraph* (the layer width and density) increase. This dependence on the topology of the *Metagraph* is stronger as the patterns get larger. But we could find no evident commonality among the "footprints" of the various *Metagraphs*.

These findings are common to several of the largest *Metagraphs*, the exception occurring mostly among the smaller projects. So far, we can say that, while smaller patterns are usually independent from a given topology and common to more repositories, others are strongly related to the structure of the *Metagraphs* and seem to occur in repositories having similar structures, in terms of diameter, layer width and density.

This outcome somehow supports the hypothesis about the intentionality of patterns: smaller patterns are direct product of developer decisions (they decide to involve one, two or three branches in some operation), while larger patterns emerges where the topology of the *Metagraphs* can support them.

A further analysis of each project, which combine the characterization of the *Metagraph* topology and its patterns with information about developer activity history and state of the software (bug tracks, release issues, etc.) could potentially achieve interesting novel insights on the collaborative development process.

R.Q. 2 — Does the structure of DVCS evolve over time?
Answer — Figure 7 shows that patterns mostly appear later in time, if not "in space". We find an interesting distinction between the timing of codebase evolution and the changes in its commit topology, at least as described in terms of *Metagraph* layers. The number of layers appears to grow faster as the project get older, which may mean that authors get more confident about merging and branching practices, or simply that more authors join a project.

We cannot attempt a generalization of this trend, because of the limited size of our sample and because of what we can consider an "internal bias" of several large repositories. We found that many of them have been automatically converted to GIT from a pre–existing CVCS. They thus initially exhibit a mostly linear topology which, *e.g.* for long–lasting successful projects, can encompass a significant portion of their total age.

Wherever the topology starts becoming complex and the *Metagraphs* denser, we see that layers do not subscribe to any regularity w.r.t. the pace of collaboration. We find layers whose time span is of few seconds and others which encompass several months. This fact may suggest that automatic merging is used in the first case. But, depending on the number of

separate branches belonging to the layers, it may simply reveal highly synchronous development activity.

Thus, if we can see that larger patterns do tend to occur later in time w.r.t. smaller ones, we cannot answer so far an interesting question: whether is there a feed–back loop between the structural complexity of a commit history (the *Metagraph* getting longer and denser) and the behavior of the developers (the fact that they branch and merge within shorter time).

We think that deepening this kind of analysis may reveal specific practices of integration and development which may affect the quality of the code, either positively or negatively.

R.Q. 3 — *Is the occurrence of patterns correlated with increased concurrent development activities?*
Answer — We found some apparently conflicting evidences in our outcomes, summarized in Table VI.

On the one hand, we see that pattern *metaedges* present a higher concentration of authors w.r.t. most of other *metaedges*. On the other hand, they do not seem to carry a particularly high number of internal commits. Based on the first observation, we can say that patterns do identify portions of the commit history where authors collaboration becomes more evident. At the same time, quite clearly higher collaboration does not entail a higher number of commits per branch.

Our hypothesis — which will need a more thorough analysis of the single projects to be confirmed — is that commits that brings most novelties to a codebase are made by fewer authors, who work in branches which do not directly end up in patterns, but merge with other "local integration" branches, which then lead the modifications to the main integration structures.

Thus, *metaedges* which comprise higher numbers of authors do not include higher numbers of commits. This is an interesting finding that open a novel perspective on how to determine the strength and the extent of author collaboration in a distributed project. By combining the analysis of author presence in *metaedges* with, for instance, code–based analysis about authors modifying the same files or components, it is possible to deepen the comprehension of collaboration practices in developer communities.

R.Q. 4 — *Are there structural similarities among DVCS histories?*
Answer — We can positively answer this question and from two diverse perspectives.

First, as Table IV shows, the structural properties of commit histories are more correlated with the size of the developer community than with the number of commits they produce. Thus it is reasonable to think that projects whose community size is close would exhibit structures of similar richness, at least from the standpoint of aggregate measuring.

Then, we find the same patterns in otherwise very diverse software repositories. Figure 6 shows that increment patterns tend to occur more, but repositories with a richer structure tend to have anyway a higher number of occurrences of both categories. The occurrence of same patterns in unrelated software repositories suggests that development practices of different teams produce similar topologies in the repositories. Common patterns across repositories may reveal common

vantage points or flaws in the way the software is developed, which may impact the quality of the software product itself.

Patterns that rarely occur in our repository sample are interesting as well. Their occurrence may be related to a particular necessity or may happen only in specific topologies. If further analysis found that they present some drawback, it would be interesting to understand which structural configuration let them emerge, in order to devise better practices.

D. Threats to validity

The reasons behind the detection of patterns in commit histories may be questioned, given the absence of evidences that support their relevance. In this paper, our main effort is giving some empirical evidence of the fact that these common sub–structures occur in complex development histories, though they may be hidden in a standard commit graph topology.

We present results which concern patterns of maximum size equal to 10. It is certainly feasible and interesting to scale up, though the computation of all possible polygons of a given size gets exponentially harder as the size increases. Anyway, the main purpose of the present work is to show relevant characteristics that, to some extent, are common to pattern of different size and are mainly due to their topological properties.

Our repository sample is of limited size, thus some of our results may not generalize on larger ensembles. It has then been chosen with no known bias towards any specific topological structure. Due to the novelty of the analysis, though, it is possible that we are not aware of specific features of the *Metagraph* topology, which somehow affect the emergence of the patterns.

Finally, the toolset we used to perform the computations has been developed by us and manually tested. We cannot exclude the presence of unnoticed bugs which could affect the correctness of our results. The subgraph detection algorithm has been provided by its author and has not been thoroughly tested by us.

V. RELATED WORK

The works which use graph–based techniques to analyze repositories focus either on characterizing the sourcecode, or on finding patterns in the social networks of developers.

In the first group, Posnett *et alii* propose models derived from ecological inference to analyze code at different hierarchical levels (files, packages, modules) [6]. They show that properties inferred at a given level may not hold at a different one or often be mistakenly considered to hold in general. Demeyer *et alii* [7] propose metrics to detect refactoring. Valverde e Solé [8] show how large scale software architectures can be modeled by dynamic logarithmic networks.

These and similar works focus on the content of contributions, rather than on the topology of commit histories.

In the second group, Posnett *et alii* propose graph–based models to infer developer focus [9], showing correlation with bug occurrences and issue solving performance. Bhattacharya *et alii* [10] combine the analysis of code organization and developer networks. They characterize both in terms of graph

metrics and they show how it is possible to predict several indicators of software quality by using these metrics. In [11] the authors analyze how different social organizations of developers impact the quality of the development in open source communities.

Several relevant works target open source software development [12], [13]. A recent paper [14] analyze the social structure of developer networks on a large sample of GITHUB projects. These works apply complex network theory to the analysis of interactions among developers and to the characterization of their contribution to projects.

A thorough analysis of GITHUB–based software development, with a deep comparative analysis of centralized and decentralized versioning systems is given in [15].

Though recent publications pay more and more attention to GIT–based repositories and their distributed development paradigm [1], [16], to the best of our knowledge no study focuses on the characterization of the topology of commit histories.

VI. CONCLUSION

Decentralized version control systems produce structurally rich commit graphs. The commit history of projects that use these systems is thus a highly non–linear graph, whose topology can be analyzed by means of techniques, which are typical of complex graph analysis.

As for many other domains, rich and complex commit histories incorporate recurring substructures that reveal similarities among otherwise unrelated projects. They characterize the development process from a purely topological standpoint. We discuss in this paper the reasons why the analysis of commit graph topology is relevant and the challenges of such a task.

We define the *Metagraph*, a novel data structure that makes it possible to perform a topological analysis of commit history graphs, in order to detect recurrent subgraphs hidden in their structure. We define and analyze several topological properties of the *Metagraphs* and we identify a class of subgraphs that we call *patterns*, which may be consider building blocks of the very topology of *Metagraphs*.

We find empirical evidences of the recurring presence of several patterns in a sample of open source GIT repositories available on GITHUB. We analyze the characteristics of these patterns and their relations with the properties of the repository *Metagraphs*. Our results support the conclusion that commit histories of otherwise unrelated projects are characterized by rich topologies, which exhibit similar properties and feature common patterns.

These findings open several different research directions. We plan to dig further the relation between patterns and properties of commit graphs, such as number of commits, authors and size of commit changesets. We think it is possible to devise novel models to characterize developer collaboration, which are based on common contributions to the same *metaedges* or patterns of a given *Metagraph*.

The novel kind of analysis we propose is not an alternative, but rather a complement to all existing techniques. By focusing entirely on topological features, it can guide to new insights on the emergent properties of distributed collaborative development.

REFERENCES

[1] E. Shihab, C. Bird, and T. Zimmermann, "The effect of branching strategies on software quality," in *Proceedings of the ACM-IEEE international symposium on Empirical software engineering and measurement*. ACM, 2012, pp. 301–310.

[2] C. Bird, P. C. Rigby, E. T. Barr, D. J. Hamilton, D. M. German, and P. Devanbu, "The promises and perils of mining git," in *Mining Software Repositories, 2009. MSR'09. 6th IEEE International Working Conference on*. IEEE, 2009, pp. 1–10.

[3] I. Wegener, *Complexity Theory: Exploring the Limits of Efficient Algorithms*. Springer, 2005.

[4] J. Howison, M. Conklin, and K. Crowston, "Flossmole: A collaborative repository for floss research data and analyses," *International Journal of Information Technology and Web Engineering*, vol. 1, pp. 17–26, 07/2006 2006.

[5] J. A. Grochow and M. Kellis, "Network motif discovery using subgraph enumeration and symmetry-breaking," in *Research in Computational Molecular Biology (RECOMB07)*, ser. Lecture Notes in Computer Science, vol. 4453. Springer-Verlag, 2007, pp. 92–106.

[6] D. Posnett, V. Filkov, and P. T. Devanbu, "Ecological inference in empirical software engineering," in *ASE*, 2011, pp. 362–371.

[7] S. Demeyer, S. Ducasse, and O. Nierstrasz, "Finding refactorings via change metrics," in *ACM SIGPLAN Notices*, vol. 35/10. ACM, 2000, pp. 166–177.

[8] S. Valverde and R. Sole, "Logarithmic growth dynamics in software networks," *EPL (Europhysics Letters)*, vol. 72, p. 858, 2005.

[9] D. Posnett, R. D'Souza, P. Devanbu, and V. Filkov, "Dual ecological measures of focus in software development," in *Proceedings of the 2013 International Conference on Software Engineering*. IEEE Press, 2013, pp. 452–461.

[10] P. Bhattacharya, M. Iliofotou, I. Neamtiu, and M. Faloutsos, "Graph-based analysis and prediction for software evolution," in *Proceedings of ICSE '12*, ser. ICSE '12, 2012, pp. 419–429.

[11] S. Valverde and R. V. Solé, "Self-organization versus hierarchy in open-source social networks," *Phys. Rev. E*, vol. 76, p. 046118, Oct 2007.

[12] A. Mockus, R. T. Fielding, and J. Herbsleb, "A case study of open source software development: the apache server," in *Proceedings of the 22nd international conference on Software engineering*, ser. ICSE00. New York, NY, USA: ACM, 2000, pp. 263–272.

[13] C. Rodriguez-Bustos and J. Aponte, "How distributed version control systems impact open source software projects," in *Mining Software Repositories (MSR), 2012 9th IEEE Working Conference on*. IEEE, 2012, pp. 36–39.

[14] F. Thung, T. Bissyande, D. Lo, and L. Jiang, "Network structure of social coding in github," in *Software Maintenance and Reengineering (CSMR), 2013 17th European Conference on*, March 2013, pp. 323–326.

[15] C. Brindescu, M. Codoban, S. Shmarkatiuk, and D. Dig, "How do centralized and distributed version control systems impact software changes?" in *ICSE'14*, 2014 (to appear).

[16] L. Dabbish, C. Stuart, J. Tsay, and J. Herbsleb, "Social coding in github: transparency and collaboration in an open software repository," in *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work*. ACM, 2012, pp. 1277–1286.