Dual Ecological Measures of Focus in Software Development

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***Abstract*—Work practices vary among software developers. Some are highly *focused* on a few artifacts; others make wide-ranging contributions. Similarly, some artifacts are mostly authored, or *"owned"*, by one or few developers; others have very wide ownership. Focus and ownership are related but different phenomena, both with strong effect on software quality. Prior studies have mostly targeted ownership; the measures of ownership used have generally been based on either simple counts, information-theoretic views of ownership, or social-network views of contribution patterns. We argue for a more general conceptual view that *unifies* developer focus and artifact ownership. We analogize the developer-artifact contribution network to a predator-prey food web, and draw upon ideas from ecology to produce a novel, and conceptually unified view of measuring focus and ownership. These measures relate to both cross-entropy and Kullback-Liebler divergence, and simultaneously provide two normalized measures of focus from both the developer and artifact perspectives. We argue that these measures are theoretically well-founded, and yield novel predictive, conceptual, and actionable value in software projects. We find that more focused developers introduce fewer defects than defocused developers. In contrast, files that receive narrowly focused activity are more likely to contain defects than other files.**

I. Introduction

Developers are the lifeblood of open source software, *OSS*, and their contributions are vital for OSS to thrive. Rather than being assigned tasks by management, OSS developers are generally free to choose the style, focus, and breadth of their contributions. Some might be quite focused, working on one specific subsystem; others may contribute to many different subsystems. An device driver expert, for example, may contribute very specialized knowledge to an open source project, focusing on only a few files or packages. His contributions to a small subset of modules[1] may be his only contribution during his tenure with the project. In contrast, a project leader may work on a variety of different tasks touching many modules within a project. While OSS developers are free to choose their contribution styles, such choices are not inconsequential, especially to the central issue of *software quality*.

A dominant theme emerging from previous work in this area is *module ownership* [1], [2], [3]. Low ownership of a module, *i.e.*, too many contributors, can adversely impact code quality. There is, however, an entirely different perspective, *developer's attention focus*, which is relatively unexplored. Human attention and cognition are finite resoucres [4]. When different tasks are simultaneously engaged, they can compete for mental resources and task performance can suffer [5]. A developer engaged in many different tasks carries a greater cognitive burden than a more focused developer. Interestingly, the developer and module perspectives are, conceptually symmetric, dualistic views of **focus**. From a module's perspective, strong ownership indicates a strong focused contribution. We refer to this as *module activity focus*, or $\mathcal{MAF}$, a measure of how focused the activities are on a module. Symmetrically, we refer to the *developer's attention focus*, or $\mathcal{DAF}$, a measure of how focused the activities are of a particular developer.

A surprising, but natural analogy for $\mathcal{MAF}$ and $\mathcal{DAF}$, are predator-prey *food webs* from ecology. In a sense, modules are predators that "feed upon" the cognitive resources of developers. As the number of developers contributing to a module increases, the diversity of cognitive resources upon which the module "feeds" also increases; likewise, a developer is a "prey" whose limited cognitive resources are spread over the modules that "prey" upon her.

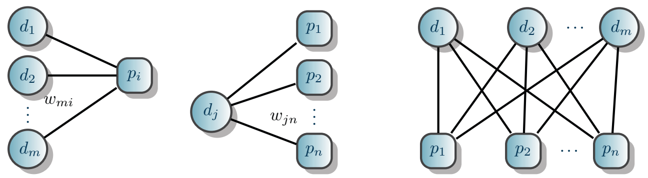
Ecosystem diversity is of great interest to ecologists. Williams and Martinez call the roles complexity and diversity play "[o]ne of the most important and least settled questions in ecology." [6] This diversity has two symmetric perspectives, both from a prey's perspective, and a predator's perspective. Ecologists have developed sophisticated symmetric measures of predator-prey relationships, drawing upon ideas such as entropy and Kulback-Leibler divergence, that simultaneously capture both perspectives. We adapt these measures for software engineering projects into the metrics $\mathcal{MAF}$ and $\mathcal{DAF}$.

In this work, we employ the methodology presented by El Emam to validate our measures [7]. In particular, we show that the $\mathcal{DAF}$ and $\mathcal{MAF}$ measures succeed in distinguishing important cases that extant measures don't capture. We make the following contributions:

- We adapt terminology and motivation from ecology, based on bipartite graphs;
- We incorporate and generalize previous results on developer and artifact diversity;
- We provide easy to compute measures of focus, $\mathcal{MAF}$ and $\mathcal{DAF}$, normalized to facilitate comparison within and across projects;
- We show these measures more precisely capture outcomes relevant to software researchers and practitioners.

This novel analysis simultaneously considers focus both from the *artifact* perspective and the *author* perspective. Researchers can use our $\mathcal{MAF}$ and $\mathcal{DAF}$ metrics to more

[1]We use modules to mean either packages or files, depending on the context.



(a) (b) (c)

Fig. 1: Graphical representation of commits from multiple developers to a single package (a), from a single developer to multiple packages (b), and their bipartite representation (c).

precisely evaluate how attributes of developer experience and focus contribute to outcomes of interest. Managers could also use these metrics to assess whether the degree of focus each developer exercises is in alignment with their expectations.

Research Outline Existing measures such as ownership and diversity only partially capture developer focus. Consider, for example, device drivers. They are small but intricate and will likely require "focused" work. If we measure the focus from solely the perspective of the module (the driver source code), we may be misled. If a single developer $\mathcal{D}$ contributed most of the coding activity in a driver module, then traditional ownership measures will indicate that the driver has received highly focused activity. However, if $\mathcal{D}$ is a prolific contributor, then the contribution $\mathcal{D}$ makes to the driver may not reflect focused attention. Indeed, $\mathcal{D}$ may have been distracted by many tasks, and the quality of the activity in the driver may be compromised.

Measuring focus solely from the developer's perspective is also insufficient. The attention of a particular developer may be highly focused on just a few files. However, if those activities make insignificant contributions, say a few lines out of thousands, then we should describe these contributions as minor in comparison to those who contribute the bulk of the code. Given equal overall contributions, a developer whose attention is focused on a small subset of the code base is viewed as exhibiting greater focused attention than the developer that contributes more uniformly.

Our Goal: Simultaneously study the module activity focus and developer attention focus in OSS.

We introduce the $\mathcal{MAF}$ and $\mathcal{DAF}$ measures in Section III. To understand them we mount a detailed study of module activity and developer attention focus in OSS projects. Starting from a combined $\mathcal{DAF}$ and $\mathcal{MAF}$ perspective, we use regression modeling to tease apart the effects of $\mathcal{MAF}$ and $\mathcal{DAF}$ on software quality and answer the questions delineated below.

Our measures enable us to characterize the attention focus of developers as broad or narrow. In particular, we ask if the leaders, or people with top involvement in open source projects are distinguishable by this measure?

Research Question 1: Do project leaders exhibit broad or narrow attention focus? What about the top developers?

The effect of focus and collaboration on defects has been studied in the past. Some papers use social network models of developer collaborations; others use ownership measures of contributions by developers. Complex network measures such as degree centrality and betweenness are difficult to interpret and act upon. Ownership measures are better, but they ignore the effect of developer attention focus. Simultaneously modeling the diversity of both sides of the developer-module contributions using $\mathcal{MAF}$ and $\mathcal{DAF}$, allows us to tease apart the effect of each separately. First, from the developer perspective:

Research Question 2: Do developers with narrow attention focus create fewer defects?

The symmetry of our measures allows us to also ask the converse, from the *module* perspective:

Research Question 3: Are modules that receive narrowly focused activity less defective?

In summary, our goal here is to understand and generalize previous results on developer focus in software development contribution networks, realizing it is two-fold. We draw insights from similar conceptual structures that have been developed in ecology on specialization and expect that this will lead to more intuitively appealing and discerning measures of contribution patterns. We begin by introducing the basic concepts of *contribution* and *ecological networks*.

Contribution Networks These networks model the total number of contributions made by each developer to each module over a specific period of time. Figures 1(a) and 1(b) illustrates a contribution network as a bipartite network consisting of modules and developers. Figure 1(c) shows a network formed by the many-to-many relationships of numerous developers, each working on numerous modules. Social network analyses have been applied to these networks [8], [9], using metrics largely derived from one-mode projections, which project the two-mode networks into either developers alone or modules alone. Instead, we use ecology-based measures which preserve their bipartite nature.

Ecological Networks In the field of ecology, interaction networks relate predator to prey, pollinator to pollen, parasite to host, or simply organism to resource [10], [11], [12]. These networks usefully capture resource-consumption relationships, and their effects on the relative abundance of different species in an ecosystem. They can, *e.g.*, help quickly identify species critical to ecosystems, or species whose survival is threatened.

In our context, we view artifacts as "consumers", and developers' resources as the "food source". We asume that cognitive capacity is limited, and no one can work an unlimited amount of time. If a person's capacity is excessively spread out or diluted, two factors come into play. First, as diversity of an individual's contribution targets increases, a given individual can only contribute a proportional amount of time to each target. Secondly, cognitive limitations, such as the difficulty of context-switching, may drive down the quality of each contribution [13]. From the consumer's perspective, a particular module clearly benefits from contributions from a greater diversity of developers, *i.e.*, there is more "food" for the consumer. On the other hand, the contributions from each developer creates additional workload for the other contributors, as they must also understand these contributions, so additional contributors make everyone who "feeds" this module have to work harder, and thus provide less "food". Thus, the straightforward analogy from food webs is complicated by cognitive limitations that introduce non-linear interference between contribution targets and contributors.

However, the above analysis-by-analogy with "food" and "consumption" highlights the two perspectives on focus in contributor networks. The *developer* focus looks at how focused developers are in their contributions, and the *module* focus considers how focused the contributions to an artifact are. We frame our contributions by first presenting existing work in this area before we launch into the theory behind our new measures.

II. Related Work

Most previous work in this area has centered around the aggregation of ownership, largely considering the dominant author as a measure of artifact authorship. Our work most closely relates to recent work by Bird *et al.* [3], Rahman *et al.* [2], and by Mockus *et al.* [1]. These works study the relationship of quality to code ownership, from an *artifact* perspective. Bird *et al.* focus on *minor contributors*, *viz.*, those who contribute less than 5% of the content of an artifact, and finds that these play a strong role in defects. However, this perspective ignores the details of the contributions of these minor committers, and in fact is agnostic about the other activities of these contributors. What if a minor contributor d_1 contributed to a module f but didn't do anything else? Then d_1 is a highly focused minor contributor. On the other hand, a minor contributor d_2 to f may in reality have contributed major changes to other modules. Bird *et al.* ignore this distinction; we in fact find that d_1 is less likely to produce defects than d_2.

Mockus *et al.* studies the risk of software changes by defining a measure that considers a developer's overall experience weighted by their experience with a particular modification request. Rahman *et al.* take a similar perspective, focusing on a developer's experience and ownership with a specific file as an indicator of quality of that file, regardless of the developer's other activities. Rahman *et al.* adapt the measures of Bird and Mockus; specialized experience measures the dominant contributor's contribution to a particular artifact, and general experience is an adaptation of Mockus' weighted experience measure. The findings in Rahman *et al.* are generally consistent with Bird *et al.*, and have similar limitations.

Shannon's entropy was originally intended to quantify the information content in a signal. The idea of using entropy to measure properties of software evolution has a long history [14], [15]. It has been used in numerous software engineering contexts; for space reasons we limit this discussion to some of the most recent efforts. Entropy has been applied to source code to model readability [16] and measure the quality of modularization [17]. Hassan and Holt applied *normalized* entropy to a sliding time window of source code changes to capture the commit state of a project and used linear regression to predict defects in several open source projects [18]. Canfora *et al.* used entropy to study the relationship between several factors, including refactoring, design patterns, and the number of contributers, and the entropy of changes as defined by Hassan and Holt [19]. The experiments yielded mixed results.

Taylor *et al.* introduced *author entropy* as discussed in the introduction [20]. Krien *et al.* extended the concept by defining author entropy across the distinct programming languages that a developer contributes code to within a project [21]. Their analysis showed a clear negative relationship between language author entropy and lines of code contributed.

Hindle *et al.* use topic analysis to study "what" a developer is focused on but their work does not capture the degree to which a developer is focused on specific artifacts [22]. Others have also studied the contributions of individual developers to artifacts. Pinzger *et al.* studied the effect of network metrics taken over the contribution network on software failures [8]. However, their results do not show significance of these measures for prediction of failure proneness even though they are significant in a linear regression model of defect counts. Consequently, it is difficult to derive any direct understanding of the relationship between the aforementioned measures and defect proneness [23]. Cataldo *et al.* build on earlier work in this area using network measures to more precisely define software and work dependencies.

Ecology has inspired other software engineering work. Calzolari used dynamic predator-prey models to study maintenance effort [24]. Lawrance *et al.* leveraged predator-prey relationships in a study of how *information foraging theory* can apply to software maintenance [25]. In this theory, developer's are modeled as predator that seeks its information prey. Posnett *et al.* studied aggregation in SE models and the threat of ecological inference risk [26]. Baudry and Monperrus described several approaches for ecologically inspired software engineering [27].

Our work takes a unified approach to focus and ownership combining artifact and developer perspectives. This leads to important new findings. After we present our theory below we will discuss in detail how our work builds upon existing measures.

III. Theory

In this paper, we consider the relationships between developers and modules. For expository purposes, we use the term *module* in a the generic sense to represent a tangible unit of code relevant to the research question. *Module* could refer to a file, a package, a component, or even simply a function.

An individual developer is denoted by d_j, for $j \in 1 \dots m$ and an individual module by m_i, for $i \in 1 \dots n$. The total contribution count to module i by developer j is denoted by w_{ij}. Summing over all developers and all modules yields the total number of contributions to the system as $A = \sum_{i=1}^{n} \sum_{j=1}^{m} w_{ij}$. We can also calculate the total number of contributions that developer j makes to the system by $D_j = \sum_{i=1}^{n} w_{ij}$. Similarly, the total number of contributions made to module i by all developers is denoted by $M_i = \sum_{j=1}^{m} w_{ij}$.

The contribution w_{ij} can be measured in lines of code, commits, or any other measure of contribution relevant to the studied context. In this work, we measure proportion of contribution as the number of commits contributed by each author.

<u>Diversity</u> This measure is conceptually based on Shannon's entropy, which measures the degree of disorder or surprise (*viz.*, information) in a system. Theoretical ecologists were among the first to employ Shannon's entropy as a measure of diversity in a species [28]. A straightforward explanation of what ecologists mean by diversity can be found in a recent discussion by Camargo [29]. We summarize here for the purposes of clearly translating the intuition to a software engineering setting. Camargo presents the definition as follows:

$$H(\text{Species Diversity}) = -\sum_{i=1}^{S} p_i \log_2 p_i$$

Where S represents the total number of distinct species and p_i is the proportion of individuals that are of species i. The definition of author entropy given by Taylor *et al.* is precisely the concept of diversity from ecology. Compare the above to the definition due to Taylor *et al.* we can see that where ecologists refer to *species* and *individuals*, Taylor refers to *developers* and *ownership*. If all species are equal in number, then diversity is high, if a particular species dominates then the diversity measure will be low. With respect to *author entropy*, however, diversity simply measures the uniformity of the commits relative to each author. If one author makes most of the commits across a system, then low diversity conveys that one author dominates the commit activity. Similarly, we can also consider the diversity of authorship commit activity with respect to a module. A module that has only one author is not diverse at all, and a module with many authors has a high degree of diversity. Simply, diversity captures commit behavior for *either* authors over a module, or modules over an author.

Using the notation given above and in Figure 1, we formulate two distinct definitions of diversity, H_{d_j} captures the diversity of contributions of author d_j to all modules, and H_{m_i} captures the diversity of contributions to a module m_i from all authors; these are defined as follows:

$$H_{d_j} = -\sum_{i=1}^{n} \left(\frac{w_{ij}}{D_j} \ln \frac{w_{ij}}{D_j} \right) \quad , \quad H_{m_i} = -\sum_{j=1}^{m} \left(\frac{w_{ij}}{M_i} \ln \frac{w_{ij}}{M_i} \right)$$

<u>Specialization & Focus</u> Specialization, in a general sense, is the opposite of diversity; the more specialized a developer's behavior, the less diverse is his contribution to a project. This property, proposed by Bluthgen *et al.* [30] in an ecological setting, can be measured naturally in a bipartite graph formulation. To distinguish our use from the terminology in ecology, and to better reflect the actual cognitive phenomena of concern in software development, we prefer the term *focus*.

Simply using diversity measures applied to both sides of the contribution network to measure focus, however, is not advisable. As Bluthgen *et al.* point out, this approach is undesirable in an ecological setting; their arguments also apply in a software development setting. An appropriate measure of focus in software development should not only consider the diversity of artifacts that a developer interacts with, but also, the overall amount of activity for each artifact. A developer who only commits a few times to a popular package with many commits, is *less* specialized than a developer who makes similar commits to an unpopular package. A good measure of focus should increase when a developer makes most of the contributions to a package compared with others who also contribute to that package. To this end, we measure the *difference* between the distribution of commits made by a developer to all modules and the distribution of commits to the system represented by those modules.

<u>Kullback-Liebler Divergence</u> Kullback Liebler divergence, or *relative entropy*, measures the difference between two probability distributions. For probability distributions P and Q the Kullback Liebler Divergence (*KL*) is defined as:

$$D_{KL}(P||Q) = \sum_i P_i \ln \frac{P_i}{Q_i}$$

KL is a measure of the expected number of extra bits that are required to code samples from P when using a code based on Q. Bluthgen *et al.* define a species level diversity measure, d, using the KL Divergence. We exploit this measure in our context to relate our two probability distributions of interest.

<u>Our Measures: $\mathcal{DAF}$ and $\mathcal{MAF}$</u> We introduce two measures: *Developer Attention Focus* , or $\mathcal{DAF}$, measures the divergence from the developer perspective, *viz.*, the degree of focus a developer exercises with respect to the artifact side of the network. From the artifact side, *Module Activity Focus* , or $\mathcal{MAF}$, measures the degree to which a module receives focused attention. We define the proportion of commits made by developer j to module i as $q'_{ij} = w_{ij}/D_j$ and the proportion of commits made to each module i as $r'_{ij} = w_{ij}/M_i$. The total proportion of commits to each package is $r_i = M_i/A$ and the total proportion of commits by each developer is $q_i = D_j/A$.

We adapt the Bluthgen *et al.* notation to be compatible with ours and substitute δ_j and δ_i in place of d to avoid confusion and to convey clearly which side of the network each metric is associated with. This (un-normalized) measure compares the distribution of the interactions with each network partner, *viz.*, developers and modules, to the overall partner contribution,

$$\delta_j = \sum_{i=1}^{n} \left(q'_{ij} \ln \frac{q'_{ij}}{r_i} \right), \qquad \delta_i = \sum_{j=1}^{m} \left(r'_{ij} \ln \frac{r'_{ij}}{q_j} \right).$$

$\mathcal{DAF}$ Intuition The intuition behind these measures is straightforward, seen clearly after a small transformation; using δ_j (un-normalized $\mathcal{DAF}$) as an example we obtain

$$\begin{aligned}\delta_j &= \sum_{i=1}^{n} \left(q'_{ij} \ln q'_{ij} - q'_{ij} \ln r_i \right) = \sum_{i=1}^{n} q'_{ij} \ln q'_{ij} - \sum_{i=1}^{n} q'_{ij} \ln r_i \\ &= \left(-\sum_{i=1}^{n} q'_{ij} \ln r_i \right) - \left(-\sum_{i=1}^{n} q'_{ij} \ln q'_{ij} \right) \\ &= \left(-\sum_{i=1}^{n} \frac{w_{ij}}{D_j} \ln \frac{M_i}{A} \right) - \left(-\sum_{i=1}^{n} \frac{w_{ij}}{D_j} \ln \frac{w_{ij}}{D_j} \right).\end{aligned}$$

This measure is computed for each developer, *viz.*, we fix j, and it is computed over all modules. There are two terms in the δ_j equation, which merit separate explanation.

The left term is the *cross entropy* of developer j's contributions with the module level contributions from all developers. The intuition is that if the proportion of a developer's contributions to each module are similar in distribution to the proportion of commits to each module overall, then we are unsurprised: the developer's contributions mimic the project as a whole. He works less on modules that are just a small part of the overall system and works a great deal on the more substantial modules. On the other hand, if the distributions are dramatically different, then the developer's contribution is unexpected, increasing cross entropy, and hence, the focus metric. If, *e.g.*, he works solely on modules that comprise just 25% of the system, then his contributions are out of proportion and should be seen as focused.

The right term corrects for a complication. Suppose that the above mentioned 25% of the system is spread out over many tiny modules that each represent a small fraction of the system. Then, even though our developer's contributions are disproportionate (limited to just 25% of the system), and we would not consider him focused. but rather distracted. In this case we want to penalize his focus score to reflect this distraction. This is accomplished by the right term, which is simply developer diversity as described in the previous section. The more spread out a developer is, the higher his diversity score. In summary, $\mathcal{DAF}$ is high when a developer both monopolizes packages and is not distracted by too many other packages.

$\mathcal{MAF}$ Intuition The derivation of $\mathcal{MAF}$ mirrors $\mathcal{DAF}$, so we present only the final line to aid understanding:

$$\delta_i = \left(-\sum_{j=1}^{n} \frac{w_{ij}}{M_i} \ln \frac{D_j}{A} \right) - \left(-\sum_{j=1}^{n} \frac{w_{ij}}{M_i} \ln \frac{w_{ij}}{M_i} \right).$$

This measure is taken from the complementary side of the network and is computed for each module, *viz.*, we fix i, and compute the metric over all developers. While the computation is virtually identical, it captures a different aspect of the contribution network.

The left term is the *cross entropy* of the contributions to the module, with the developer contributions to the system. As before, if the distributions are similar, then the module receives minimal contributions from developers who are not major contributors to the overall system, and sufficient attention from those developers most responsible for the system. In this case, the module's focus is low, and we're not particularly surprised. For example, if a `README` file has received a fraction of a percent of the commits from a particular developer, we're not surprised so long as the file isn't dominating that developer's attention. If, in fact, it is dominating, then this excess attention is *focused attention* to the module. Similar to $\mathcal{DAF}$, the right term penalizes the focus for the diversity of contributions. Modules equally contributed to by multiple developers do get less focused attention than modules with high ownership. In summary, $\mathcal{MAF}$ is high when a package monopolizes a developer's attention and receives little attention from other developers.

$\mathcal{MAF}$ and $\mathcal{DAF}$ are both normalized by the theoretical maximum and minimum possible values of the measures. For the max, $\delta_{j_{max}} = ln\ {}^{A}/_{D_j}$ and $\delta_{i_{max}} = ln\ {}^{A}/_{P_i}$. The theoretical minimum value of 0 is typically not attainable in the case where the proportional counts are based on integer values, as is the case here, so a heuristic is used to find a suitable minimum (See [30] for more detail)[2]. Using these minimum and maximum values the δ_j is standardized to a 0 to 1 range with the following normalization:

$$\mathcal{DAF}_j = \frac{\delta_j - \delta_{j_{min}}}{\delta_{j_{max}} - \delta_{j_{min}}}, \qquad \mathcal{MAF}_i = \frac{\delta_i - \delta_{i_{min}}}{\delta_{i_{max}} - \delta_{i_{min}}}.$$

Since these measures specifically take into account the contributions that each developer makes and that each module receives, their values are independent of this variation within a network and can be used to compare the relative focus levels of individual developers and modules.Each metric can be interpreted as a deviation of contribution frequencies from a null model which assumes that all developer/module pairs are contributed from/to in proportion to the overall contribution to the system. In the simplest case of a fully balanced network. where all $q'_{ij} = r'_{ij}$, the theoretical minimum value of 0 will be achieved. When $q'_{ij} = r'_{ij}$ the cross entropy equals the entropy, and focus is minimized.

In Section V we discuss how our metrics related to existing work and present a small case study on a real system to help illuminate how it is able to distinguish important cases. In the next section we describe the data and methods used for the case study and for the statistical analysis in Section VI.

[2] Also the R bipartite package, http://cran.r-project.org/web/packages/bipartite/index.html

TABLE I: Apache Software Foundation projects used in this study.

Project	Releases	# Files	# Packages
Avro	1.3.2 - 1.4.1	158-238	12-17
Cassandra	0.6.0 - 0.6.8	314-332	31-33
CXF	2.11-2.3.1	3086-4097	491-598
Ivy	2.0.0 - 2.2.0	481-498	65-67
Lucene	1.9.1 - 3.0.3	1010-957	102-85
Shindig	2.0.0, 2.0.1	811-812	75-75
Wicket	1.2.7 - 1.3.7	1776-1947	240-249

IV. Data and Methodology

Data We extracted metrics often used for defect prediction for seven projects maintained by the Apache Software Foundation, listed in Table I. For each project we used the source code repository and the Jira issue tracking system to extract basic process metrics such as churn, the number of commits, and the number of developers associated with each file and package. The specific metrics used are described briefly with each model description.

Jira Jira is an issue and bug tracking system that manages a database of issue reports submitted by developers and users. Issues are of various types including new features, improvements, or defects. Jira enforces a basic development process by mapping issue reports to version control commit messages. Issue IDs extracted from version control system commit log messages are cross linked with the associated report in the Jira database. We extracted the Jira issues from the XML report available on the Apache Software Foundation's project website for each of the projects.

Version Control Version control systems, *e.g.*, Git, SVN, and CVS, facilitate collaboration among developers by maintaining and recording a history of changes. To obtain the number of commits and developers associated with each file we parse logging data retrieved from Git. We use the Jira issue IDs and the Git version control log to link issues associated with each commit to the modified files and to associate defect counts with each file in the release.

Bug-Introducing Change For defect issues in the Jira database we'd like to try to locate the files that induced the defect fixing modification. The lines of code associated with the changes that triggered such a modification are referred to as "fix inducing code" as coined by Sliwerski *et al.* [31].

To identify the fix inducing code we use the aforementioned *SZZ* algorithm and identify the commits associated with each defect fix. If a fix is associated with revision n, then we apply *git diff* to revision $n-1$ and revision n to identify the specific lines that were changed in the fix. We then use *git blame* on only the changed lines to identify the revision responsible for the fix inducing code. If the revision was changed after the defect introduction, then we do not associate post defect changes with the defect. Otherwise we associate the unique defect ID with the file in the fix inducing revision. This allows us to identify the unique defects, modulo SZZ accuracy, that can be blamed on each file in the system.

Contribution Networks We described contribution networks in Section I. To gauge the global focused attention of each developer over the life of the project we built a network using all entries in the commit graph over the full period of each project that we studied. This approach results in static focused attention values for each developer and for each module.

V. Analysis and a Case Study

With respect to the methodology described by El Emam we want to show that our new metrics $\mathcal{MAF}$ and $\mathcal{DAF}$ capture properties not captured by other metrics [7]. We discuss this in an analytical setting first and conclude this section with a case study. In Section VI, we strengthen this analysis with some statistical results.

Ownership The simplest measure of focus is module ownership which is usually measured as the proportion of contributions to a module. The developer with the highest ownership is identified as the module's owner. Not surprisingly, ownership shows no meaningful correlation with $\mathcal{MAF}$ but strong correlation with betweenness measures (see Section V); trivially, ownership cannot capture any significant nature of developer or module interaction as the measure itself considers only a single developer and module in isolation.

Betweenness In prior research, betweenness in contribution networks is used as a proxy for developer focus. It is a simple measure of module connectivity, measuring the fraction of geodesic paths between developers that pass through a module [32]. If a module was touched by fewer developers, who themselves touched few other modules, then betweenness will be low, indicating high focus. We also consider the "developer network edge betweenness" (*DNBetweenness*), a collapsed view where developers are the nodes of the graph and the modules connecting nodes form the edges. As more developers touch a file, the likelihood of betweenness goes up; so, however, does the number of commits, the code size, the number of bug fixes, and consequently, the number of defects (see Table II). Thus, betweenness, in practice, rarely adds any predictive value beyond raw developer count (see Section V).

Diversity Diversity is a more sensitive measure that represents the commit entropy of each module. Like betweenness, high diversity values implies a lack of contribution focus. Low values of diversity suggest low surprise at who is going to commit next. Diversity doesn't distinguish cases where this surprise might be important, *e.g.*, a device driver, with cases where it is largely irrelevant, *e.g.*, a `README` file.

TABLE II: Spearman rank correlation of network measures and $\mathcal{MAF}$. *(Btw=Betweeness, DNE=DNEMaxBetweenness)*

	$\mathcal{MAF}$	Ownership	Diversity	Btw	DNE	Bugs
$\mathcal{MAF}$	1.00	-0.07	-0.18	-0.19	0.05	-0.19
Btw	-0.19	-0.47	0.66	1.00	0.70	0.49
DNE	0.05	-0.49	0.85	0.70	1.00	0.53

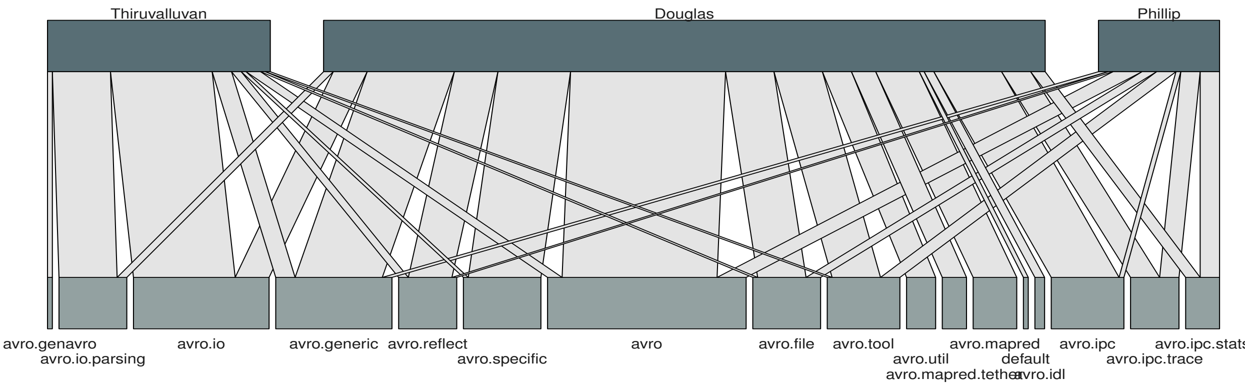


Fig. 2: The full bipartite network of Apache Avro with developers at the top and files on the bottom. Block and edge sizes represent the number of commits either from, or to, developers and packages respectively.

Experience Some measures of experience consider a developer's system level contributions along with each contribution to an entity; specifically, Mockus' experience measure, although applied in a different setting, is the closest to ours [1]. In fact, it can be shown that this measure is equivalent to a normalization term minus the cross entropy $H(r'_{ij}, q_j)$. It does not, however, fully capture the nature of developer "focus" as it does not capture diversity, does not have a standard range, and most importantly, does not define a developer focus metric such as $\mathcal{DAF}$. Additionally, it is worthwhile to note that the dual nature of our measures permits an elegant computation, *viz.*, that the same code can be used to calculate either measure on the weighted adjacency matrix that represents the contribution network simply by transposing the matrix to obtain the dual.

Avro Case Study Apache Avro is a remote procedure call and serialization framework. Its primary purpose is to provide serialization for persistent data and a format for distributed data exchange. It is a moderately-sized project with over 200 files. We gathered 110 distinct commits of the project between Jan 2010 and Sep 2010. During that time there were only three committers to the Java code of the project. Because of its manageable size we use it here to illustrate some properties of various focus metrics. The full bipartite package level contribution network can be seen in Figure 2. Block and edge sizes in the graph represent the number of commits either from, or to, developers and modules respectively. We first consider $\mathcal{MAF}$, contrasting it to with the previously defined entropy measures, the simple proportional measure of ownership, and the concepts of node and edge betweenness, and then we discuss $\mathcal{DAF}$.

$\mathcal{MAF}$ In comparing other metrics to $\mathcal{MAF}$, ownership is the simplest to discuss; consider package `avro` in Figure 2 which is owned by Douglas with ownership of 0.78. With a $\mathcal{MAF}$ score of 0.04 we might conclude that ownership and $\mathcal{MAF}$ are inversely related. However `avro.specific` has both higher ownership, and higher $\mathcal{MAF}$. Table II shows that $\mathcal{MAF}$ and ownership are not strongly correlated.

Betweenness considers more of the network, but are also problematic. Since betweenness measures, as in Meneely *et al.* [9], do not take into account the relative contribution of each developer, they are often highly correlated with the number of developers and other "size" metrics. Further, because the developers are tightly connected by the modules, neither form of betweenness discriminates interesting cases.

Diversity is able to capture some variance in contribution that betweenness misses. Consider the packages `avro.file` and `avro.specific`. They have identical betweenness values of 0.125, suggesting that they are unfocused artifacts. Their diversity values, however, tell a different story and are considerably different for these two packages. Three developers have contributed to `avro.file` which has a diversity

TABLE III: $\mathcal{MAF}$ discriminates interesting cases better than other ownership metrics in Apache Avro.

	Ownership	Diversity	Focus $\mathcal{MAF}$	Btw	DNE Btw	Bugs
avro	0.78	0.67	0.04	0.12	1	1
avro.file	0.71	0.76	0.03	0.12	1	2
avro.specific	0.94	0.23	0.09	0.12	0	1
avro.tool	0.67	0.80	0.05	0.12	1	0
avro.ipc.stats	0.57	0.68	0.21	0.00	0	0
avro.io	0.75	0.56	0.34	0.12	0	0
avro.io.parsing	0.86	0.41	0.36	0.12	0	1
avro.genavro	1.00	0.00	0.23	0.00	0	0
avro.generic	0.75	0.72	0.01	0.12	1	4
avro.reflect	0.75	0.72	0.00	0.12	1	0
avro.util	1.00	0.00	0.10	0.00	0	0
avro.ipc	0.93	0.24	0.10	0.00	0	2
avro.mapred	1.00	0.00	0.12	0.00	0	0
avro.mapred.tether	1.00	0.00	0.10	0.00	0	0
avro.idl	1.00	0.00	0.02	0.00	0	0
avro.ipc.trace	0.60	0.67	0.14	0.00	0	0
default	1.00	0.00	0.00	0.00	0	0

score of 0.759. The width of the ribbon connecting Phillip to this package indicates that he has made a modest but significant proportion of the commits to the package, Thiruvalluvan has also made at least one commit, although his contribution is smaller. Finally, although Douglas has made most of the commits, the total number of contributions to the package is still relatively small. In contrast, `avro.specific`, has only two contributors and Douglas clearly owns the lion's share. This results in a much lower diversity value of 0.234, indicating the relative lack of surprise at who will make the next commit.

Unfortunately, diversity is insufficient to capture many examples of focus. `avro.ipc.trace` and `avro` have almost identical diversity values of 0.673 and 0.683 respectively, but their betweenness values, and the number of developers, are different. Package `avro.ipc.stats` also has a similar diversity score of 0.683 and like `avr.ipc.trace` has only two developers, thus, its betweenness value is 0. In this example, $\mathcal{MAF}$ is able to discriminate between many interesting cases that other metrics fail to capture.

$\underline{\mathcal{DAF}}$ We now turn our attention to developer focus and $\mathcal{DAF}$. From the contribution network we can see at a glance that Thiruvalluvan probably has the greatest focus. Most of his commits are focused in two packages, whereas both Douglas and Philip, do not appear to have any packages that dominate their contribution patterns. This distinction is important; clearly Douglass dominates the `avro` package and one can view the package as receiving focused contributions, however, it does not dominate Douglas' contributions to the system. Even though it is the package that Douglas has contributed to the most, it has received, at most, approximately twice the contributions of the next smaller package and there are at least three or four such packages. This is quite different from Thiruvalluvan who's largest contribution accounts for about half of his total contributions to the system. In this instance, developer diversity, *viz.*, *(author entropy)*, captures this difference nicely, ranking Thiruvalluvan as the most focused developer, and Douglas as the least focused (See Table IV). However, as with the module perspective, diversity is limited as a measure of developer focus. Consider again packages `avro.file` and `avro.specific`, which have identical betweenness values and drastically different diversity values. The $\mathcal{MAF}$ values of these packages are both fairly low at 0.034 and 0.087 respectively. The skewed contribution from Douglas yields the low diversity score indicating focused attention, but the contribution from Douglas does not represent a disproportionate focus from his perspective. It cannot be argued that Douglas is focused on this package, his efforts are spread out fairly evenly over a number of packages. So $\mathcal{MAF}$ and $\mathcal{DAF}$ measures capture focus from both the perspective of the developer and the module. A focused package is one that receives a lot of attention from few developers who devote most of their attention to that package.

Interestingly, the two packages with the highest focused activity scores are `avro.io.parsing` and `avro.io` which are both dominated by Thiruvalluvan. By simply looking at the web, we might conclude that Thiruvalluvan is something of an I/O specialist, Douglas is the project leader, and that both he and Phillip exhibit broader, less focused attention. Both the $\mathcal{MAF}$ and $\mathcal{DAF}$ scores, which are mostly low with the exception of Thiruvalluvan and his focus on I/O, support this hypothesis.

TABLE IV: $\mathcal{DAF}$ scores reflect developer role in the Avro project.

	$\mathcal{DAF}$	Diversity	#Commits	Bug Fixes	Bugs
Douglass	0.23	2.48	71	26	7
Thiruvalluvan	0.51	1.57	25	11	2
Philip	0.30	1.94	14	2	2

VI. RESULTS AND DISCUSSION

For the following research questions, we used *negative binomial regression, NBR,* to model count data against parameters of interest. NBR is a generalized linear model used to model non-negative integer responses. It is appropriate here as it can handle *over- dispersion*, *e.g.*, cases where the variance is greater than the mean in the response [33]. Our focus is on understanding the mean, within project, behavior; consequently, we view each project as a random effect in a pooled model incorporating it as a grouping factor that captures the between project variance in the response. In all cases we log transformed independent count variables to stabilize the variance and improve the model fit [33].

RQ1: Overall and top-contributor attention focus

As we saw with the Avro project, it is often the case in OSS that there is a dominant project contributor. We might expect that project leaders exhibit lower attention focus if they contribute a significant proportion of the project's code. As a developer's contribution increases, it becomes increasingly difficult to contribute a greater proportion of code than expected to the many files currently touched. The dominant contributor $\mathcal{DAF}$ for each project is listed in Table V. In each case, the focus scores of the dominant contributors are below the mean.

TABLE V: Project leaders are less focused than average.

	Ivy	Avro	Wicket	Shindig	Lucene	Cassandra	CXF
$\mathcal{DAF}$	0.17	0.23	0.20	0.08	0.19	0.09	0.14
$\overline{\mathcal{DAF}}$	0.41	0.54	0.57	0.41	0.56	0.43	0.57

To determine the level of contribution by focused devs we regressed the number of commits against the number of files touched and the developers $\mathcal{DAF}$ score. A manual examination of the data revealed that the top 5% of contributors touch significantly more files than the remaining developers necessitating the inclusion of *#files* in the regression model as a control. We can see from the model in Table VI that the $\mathcal{DAF}$ coefficient is suggestive of an effect, *viz.*, only significant at a 10% level, after controlling for the number of files touched.

So while focused developers do contribute to fewer files, even while controlling for this factor, *i.e.*, holding it constant,

TABLE VI: Developers with high $\mathcal{DAF}$ contribute less code.

$N = 107$	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.0924	0.3061	-0.30	0.7628
log(files)	1.0037	0.0366	27.43	$< 2e-16$
$\mathcal{DAF}$	-0.6511	0.3898	-1.67	0.0948

they do not contribute as much code as more broadly focused developers.

Result 1: Project leaders and top contributors tend to exhibit lower attention focus than others. The effect of attention focus on contribution falls below the 5% level standard for statistical significance, but is suggestive at the 10% level of significance after controlling for the number of files changed.

RQ2: Do narrowly focused developers create fewer defects?

To answer this question we regressed the file contribution pattern of each developer against the number of defects introduced by that developer. We are interested in the degree to which focused attention could explain their contribution of defects to the software over its lifetime. For this experiment we evaluated the entire contribution network for each project obtaining a mean attention focus score for each developer over the life of the project. We modeled the total number of induced defects attributed to each developer against the $\mathcal{DAF}$ scores, with respect to files. We limited the number of size-based control variables to avoid a high variance inflation factor *VIF* [33]. We included the number of files to control for the spread of developer focus based on the number of artifacts changed. Similarly, we include the number of commits to control for the positive relationship between the number of changes made and the number of defects.

TABLE VII: Developers with high $\mathcal{DAF}$ produce fewer bugs.

$N = 107$	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.4960	0.4544	-3.29	0.0010
log(commits)	0.3266	0.1260	2.59	0.0095
log(files)	0.6998	0.1434	4.88	$< 2e-16$
$\mathcal{DAF}$	-1.2979	0.5561	-2.33	0.0196

As can be seen from the model details in Table VII, after controlling for the number of files as well as the number of changes, $\mathcal{DAF}$ has a negative effect on the number of defects induced by a developer, *i.e.*, the more narrowly focused the developer, the fewer defects that he introduces. Our results at the package level were similar suggesting that this relationship is robust to ecological inference risk [26].

Result 2: Narrowly focused developers introduce fewer defects at both the file and package level.

RQ3: Do files that exhibit narrowly focused activity have fewer defects?

If developers with narrow focus introduce fewer defects, then we might expect that those files at the center of narrow activity focus, *i.e.*, that have a low $\mathcal{MAF}$, would have fewer defects. We considered this by regressing $\mathcal{MAF}$ and other file properties against the number of defects induced in each file, controlling for file size, the number of commits, and the number of developers. The details of the model are shown in Table VIII. Surprisingly, the direction of the coefficient is positive, *i.e.*, increasing focused activity has a *negative* impact on software quality while holding other factors constant.

We included ownership in the model to test whether this simple measure was able to capture a similar relationship with defects. We placed both ownership and $\mathcal{MAF}$ in the model last so that any collinearity with other variables would attribute the shared variance to the control. Both the ownership and $\mathcal{MAF}$ coefficients were stable in either order, however, ownership had high collinearity with the number of commits whereas $\mathcal{MAF}$ did not. We find that $\mathcal{MAF}$ accounts for four times the explained deviance of ownership in this model. When considered in concert with RQ2, this result suggests that while it is important for a developer to focus his efforts to avoid excessive unfocused contribution, it is also important for files to receive some general attention.

We also note that, in agreement with prior research, increased ownership is negatively correlated with defects. However, the effect is not statistically significant. There could be several factors driving this result. Files with high $\mathcal{MAF}$ may be more complex and are consequently naturally more defect prone. It may also be the case that if file attention is too focused, then there are simply too few eyeballs and greater diversity may be necessary to find defects [34].

Result 3: Increased file activity focus results in a greater number of defects.

Threats To Validity

We recognize a few threats. First, complex files are more defective. It would be revealing to study the relationship between code complexity and focus. However, since file complexity is typically correlated with code size, and our models take size into account, the impact on our results is likely small. While $\mathcal{MAF}$ and $\mathcal{DAF}$ may change over time, this study considers the aggregate behavior over the life of a project. This is, in part, because our measures are based on information theory, and consequently, they inherit the associated benefits and challenges. In particular, information theoretic measures are well known to necessitate substantial amounts of data to yield appropriate results. We plan to address the evolution of $\mathcal{MAF}$ and $\mathcal{DAF}$ in future work. Neither metric is suitable

TABLE VIII: $\mathcal{MAF}$ is significant after controlling for the number of changes and is positively associated with the number of defects in files.

$N = 3595$	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-4.1503	0.2499	-16.61	$< 2e-16$
log(commits)	0.8733	0.0618	14.13	$< 2e-16$
log(devs)	0.1697	0.0916	1.85	0.0639
log(loc)	0.2261	0.0290	7.81	$< 2e-16$
ownership	-0.3397	0.1901	-1.79	0.0740
$\mathcal{MAF}$	0.9430	0.2647	3.56	0.0004

when either side of the network is a singleton in which case the metrics are undefined. However, in this case, simple diversity paints a complete picture of focus.

VII. Conclusion

The focus measures we introduced have roots in ecology but are very well suited for analysis of focus in a symmetrical setting between developers and artifacts. In addition, focus used in modeling is facilitates straightforward interpretation. The effect of focus on defect introduction is particularly clear: when developer focus is higher, fewer defects introduced. With files, the effect of focus on defects is clearly not strong. This is a welcome side-effect of the artifact-developers symmetry of this measure; the joint effects of artifact and developer can be deconvolved into separate contributions so that they can be considered and reasoned about individually, while still considering their interaction within the contribution network. Finally, our focus measures can be useful in practice as an assessment tool.

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