A Methodology for Analyzing Uptake of Software Technologies Among Developers

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Abstract—Motivation: The question of what combination of attributes drives the adoption of a particular software technology is critical to developers. It determines both those technologies that receive wide support from the community and those which may be abandoned, thus rendering developers’ investments worthless. Aim and Context: We model software technology adoption by developers and provide insights on specific technology attributes that are associated with better visibility among alternative technologies. Thus, our findings have practical value for developers seeking to increase the adoption rate of their products. Approach: We leverage social contagion theory and statistical modeling to identify, define, and test empirically measures that are likely to affect software adoption. More specifically, we leverage a large collection of open source version control repositories (containing over 4 billion unique versions) to construct a software dependency chain for a specific set of R language source-code files. We formulate logistic regression models, where developers’ software library choices are modeled, to investigate the combination of technological attributes that drive adoption among competing data frame (a core concept for a data science languages) implementations in the R language: tidy and data.table. To describe each technology, we quantify key project attributes that might affect adoption (e.g., response times to raised issues, overall deployments, number of open defects, knowledge base) and also characteristics of developers making the selection (performance needs, scale, and their social network). Results: We find that a quick response to raised issues, a larger number of overall deployments, and a larger number of high-quality StackExchange questions are associated with higher adoption. Decision makers tend to adopt the technology that is closer to them in the technical dependency network and in author collaborations networks while meeting their performance needs. Future work: We hope that our methodology encompassing social contagion that captures both rational and irrational preferences and the elucidation of key measures from large collections of version control data provides a general path toward increasing visibility, driving better informed decisions, and producing more sustainable and widely adopted software.

Index Terms—choice models, social contagion, technology adoption, library migration, software supply chain

1 INTRODUCTION

Open source has revolutionized software development by creating and enabling both a culture and practice of reuse, where developers can leverage a massive number of software languages, frameworks, libraries, and tools (we refer to these as software technologies) to implement their ideas. Open source allows developers, by building on the existing work of others, to focus on their own innovation [1], [2], [3], [4], potentially reducing lead times and effort. This approach, however, is not absent of risks. For example, if a particular technology chosen by a developer is later supplanted by another, incompatible technology, the support for the supplanted technology is likely to diminish. Reductions in support for the supplanted technology result in increased effort on the part of the developer to either provide fixes upstream or to create workarounds in their software. Furthermore, the value of the developer’s creation to new downstream projects may diminish in favor of the now more popular alternative package. As a consequence, both the importance of a developer’s product and their reputation may suffer. To remediate these two risks, developers must understand how attributes of their software products may be perceived among potential and actual downstream adopters (consumers of the technology), especially in relation to alternative, competing technologies these adopters may have. It is natural, therefore, to adopt the position that open source software development should be investigated from a supply chain perspective, which also pertains to distributed decision and supply networks among different stakeholders. We refer to the collection of developers and groups (software projects) producing updates (patches and new versions) of the source code as a Software Supply Chain (SSC) [5], [6]. The upstream and downstream links from project to project are represented by the source code dependencies, sharing of the source code, and by the contributions via patches, issues, and exchange of information. While the product adoption in supply chains has been well studied [7], [8], [9], [10], little is known or understood about how developers choose what components to use in their own software projects.

As a complex dynamical system, every player in the open source ecosystem may have their specific set of preferences or biases, which can affect the ultimate outcome of wide (or narrow) adoption and/or entire abandonment of formerly popular technologies. These decisions are not only based on technical merit but the availability and accessibility of relevant information along with the tastes
of consumers (adopters). Furthermore, these SSC networks may severely limit developer choices at the particular point in time when they need to make decisions on which components or technologies to use based on what components they are aware of and how much time or inclination they have to investigate the relative merits of the possible choices. This suggests the potentially strong influence of default choice well documented in behavioral economics. Hence, in contrast to common conventions, we should not simply model the preferences of individual developers but must also take into account the complexity of the supply networks and their specific position within them.

We want to address this major gap in knowledge empirically by using a very large data source comprising version control data of millions of software projects. Our methodology involves using this data to construct software supply chain networks, identifying software technology choices, theorizing about factors that characterize the developer and the technologies they chose, and finally fitting and interpreting the models for specific technology choices and, thus, characterizing the implicit primary factors (social, behavioral, and rational) they may use to make their decision.

Despite the practical and theoretical importance of the question how developers make technology choices, the extant literature does not offer theoretical guidance on this subject. We, therefore, leverage social contagion theory, which has been effective, among other things, in clarifying key aspects of organizational adoption of technology [11], [12]. Social contagion theory mimics models of the spread of contagious diseases but apply them in the behavioral/social context instead of the physiological one. The first key concept is exposure or how widespread the infectious agent in the population. In our case the agent is a specific package and the population is the entire collection of FLOSS repositories. The exposure is critical in epidemiology because without the exposure a disease cannot spread. This brings us to

**RQ1:** Does the exposure to a technology, such as the number of FLOSS repositories in existence, the rate at which new repositories are adopting this technology, or the number of high-quality questions on StackExchange affect the decisions of the developers to adopt that technology?

The second key concept is infectiousness: a highly virulent agent is more likely to spread in a population. We deal with packages or technologies (groups of packages), so in our case we’d like to establish:

**RQ2:** Will extremely attractive package (with few open issues, short response times to issues or pull requests, heavy activity and many authors), be more likely to be adopted?

The final concept is proximity: some infectious agents may not survive the travel through air or physical barriers, thus halting their spread. In our case, the distance from a developer to a package is physical, but it may be represented the technological constraints (lack of compatibility with other packages the developer already uses), need for certain performance characteristics, or a social distance to collaborators who are working with other developers already exposed to the package or a related technology. Hence:

**RQ3:** Will proximity of a developer or a project to a package increase the rate of adoption? More specifically, **RQ3a:** will the proximity of a developer to a related technology used by a developer increase the chances of adoption? **RQ3b:** will the proximity of a developer to collaborators who already use a package or a related technology increase the chances of adoption? **RQ3c:** will the performance requirements of the project a developer is working on increase the chances of adoption of a package that has the desired performance attribute?

To answer RQs, we need to collect data on the actual choices made by developers and operationalize key theory-based measures, we need an to reconstruct the states of all public software projects that may choose the technology under study. For example, for a project that chooses Package A in January 2014, we need to establish how many other projects have used before that date (exposure), what average response time to issues the project had at that time (infectiousness), and what actions the developer making the choice to add the dependence had prior to that point in time, including her social network, technology network, etc.

To exemplify the proposed methodology, we investigate rapidly growing data-science software ecosystem centered around the R language. One of the key technology choices in this area are the data structures used to store data (in the data-science sense). R has two major competing technologies implemented in packages data.table and tidy. (a more detailed introduction of these two packages is given in Sec. 4)

Our research provides several theoretical and practical innovations. From the theoretical standpoint, the novelty of our contribution first lies in introducing social contagion theory that provides first-principles based methods to construct hypotheses and to determine measures that should affect technology adoption. The second novelty is the context in which we investigate technology choices, i.e., a complete SSC [13], [14], not restricted to a set of projects or ecosystems. Third, we use regression models to understand how macro trends at the scale of the entire SSC emerge from actual decisions the individual developers make to select a specific software technology. More specifically, as a result of contextualizing social contagion theory through SSCs, our approach provides novel measures, such as proximity in a dependency network and authorship network, questions and answers with high quality in Q&A, performance needs, and total deployments, that strongly affect the spread of technology and that were not used in prior work on library migration.

From the practical standpoint, our contribution consists of proposing a method to explain and predict the spread of technologies, to suggest which technologies are more likely to spread in the future, and suggest steps that developers could take to make the technologies they produce more popular. Developers can, therefore, reduce risks by choosing technology that is likely to be widely adopted. The support of open source software could use such information to focus on and properly allocate limited resources on projects that either need help or are likely to become a popular infrastructure. In essence, our approach unveils previously unknown critical aspects of technology spread and, through that, makes developers, organizations, and communities more effective.

In Sec. 2 we introduce the diffusion of innovation, social
contagion, and the application of choice models. In Sec. 3 we describe the dataset and how we operationalize software supply chain. Choice model theory and our candidate technology are introduced in Sec. 2.3 and Sec. 2.7 respectively. In Sec. 7 operationalization of attributes of choice model is illustrated. Sec. 5 describes and interprets the result of applying the choice model. Related work is discussed in Sec. 7 and major limitations are considered in Sec. 6. We summarize our conclusions and contribution in Sec. 8.

2 Conceptual Background

We draw on methodologies from a diverse set disciplines. The phenomena we are investigating is often called adoption [15] or diffusion of innovation [16]. Both theoretical approaches model how products or ideas become popular or get abandoned. We would like to fit such models and, in order to do so, find relevant set of predictors that have theoretical justification. Fichman [17] considered how internal factors such as resources and organization predict innovations in commercial enterprises, and DiMaggio [18] included the factor of environment as well. The adopters of the technology may influence non-adopters over time. Angst et al. [11], use the concept of social contagion [19], which consists of observation, information transmission, and learning to study spread of electronic health records. These concepts are familiar to any open source developer. More specifically, in addition to purely social contagion, we also have technical dependencies that act as strong constraints on developer actions. The signaling theory applied for social coding platforms [20], [21] provides some specific guidance as to what may motivate developers to chose one project over another. Many of the actions developers take on GitHub are focused on building or maintaining their reputation, hence they pay a particular attention to measures such as activity, numbers of participants, or “stars”.

The basic premise of social contagion theory is that developers may observe the actions and decisions of others, communicate them, and learn to emulate them over time. This premise implies that groups and individuals who are in social and spatial proximity to prior adopters are more susceptible to the influence of prior adopters of technology. This susceptibility (synonymous with potency or infectiousness of influence) is likely to result in an increased likelihood to adopt the same technology [11]. Notice, that the susceptible to influence of prior adopters represents non-rational behaviour. Rational behaviour would require developer to choose the best technology irrespective of social influences. It may also represent cognitive bias of the default choice. The developer may not know about the alternatives if their social or technical networks do not present them with an encounter with alternatives. This would represent the irrational bias toward default choice. These precursors of spread, if measured and calibrated with the actual level of technology spread, would provide the relative importance of each factor in driving the adoption and provide the understanding to help developers choose technologies wisely and provide hints on how to make their own technology more widely adopted. Fortunately, the mathematical adoption models have been developed and refined over time. A variation of multinomial regression models also called choice models [22] can be used to describe the behavior of a decision maker given a set of alternatives. Choice models have been used successfully in the fields of marketing [23], [24], [25], [26] and economics [27], [28], [29] to understand how consumers make choices. Adapting and applying these regression models to technology adoption, we focus on a developer, or more precisely, a software project as a decision maker. The actual decision is operationalized as the first among the alternative technologies that a project in a commit modifying one of the files within a repository. As with the social contagion theory, two types of predictors can be included: properties of the choice (i.e., the technology) and properties of a decision maker (i.e., the project or individual developer).

Equipped with this theoretical and modeling framework, we set out to address RQ1 and RQ2 by empirically characterizing the spread of software technology through analysis of a very large collection (VLC) of version control data introduced in [30] and curated by OSCAR project [31]. We refer to it as OSCAR-VLC. According to the curators, OSCAR-VLC approximates the entirety of public version control and includes major forges such as GitHub, BitBucket, GitLab, Bioconductor, SourceForge, now defunct Googlecode, and many others and currently contained over 46M projects at the time of analyses. OSCAR-VLC production involves discovering [31] and cloning the projects, extracting Git objects from each repository, and then storing these objects in a scalable key-value database.

OSCAR-VLC is used to construct the SSC [32], [33] by determining dependencies among software projects and developers, then by characterizing these projects according to their technical characteristics and supply chains. The social contagion and signaling theories allow us to select meaningful measures for the decision makers and for their choices. (We present our measures in Sec. 4.1)

3 Constructing Software Supply Chains

Source code changes made in software projects are recorded in a VCS (version control system) used by the software project. Many of the projects are using git as their version control system, sometimes with historic data imported from SVN or other VCS used in the past. Code changes are typically organized into commits that make changes to one or more source code files. Internally, the Git database has three primary types of objects: commits, trees, and blobs [34]. Each object is represented by its sha1 value that can be used to find its content. The content of a blob object is the content of a specific version of a file. The content of a tree object is, essentially, a folder in a file system represented by the list of sha1s for the blobs and the trees (subfolders) contained in it. A commit contains the sha1 for the corresponding tree, a list of parent commit sha1s, an author string, a committer string, a commit timestamp, and the commit message. Fig. [1] illustrates relationships among objects described above.

We utilize all Git objects (1.1 billion commits and 4 billion of blobs and trees) from OSCAR-VLC to construct

1. placing a star on a GitHub repository allows a developer to keep track of projects they find interesting and to discover similar projects in their news feed.

2. bitbucket.org/swsc/overview
the relevant supply chain, social, and adoption measures. For our analysis we create mappings among these objects and their attributes, e.g., filename to associated blobs.

### 3.1 Software supply chain

In traditional supply chains [35], [36], [37], [38], [39], the networks include material, financial and information relationships. Similar concepts can be operationalized in the software domain, with developers or projects representing the nodes and information transfer or static dependencies among projects representing links. Based on the characteristics of software domain, especially the open source community, and the ability to measure various attributes relevant to technology adoption, we consider two different types of network relationships: dependency networks, and authorship networks.

### 3.2 Measuring the dependency network

While many types of static dependencies exist, here we focus on explicit specification of the dependency in the source code. For example, ‘import’ statements in Java or Python, ‘use’ statements in Perl, ‘include’ statements in C, or, as is the case for our study, ‘library’ statements for the R language.

We analyze the entire set of 4 billion blobs existing in the database at the time of the analysis using following steps:

1. Use file to commit map to obtain a list of commits (and files) for all R language files by looking for the filename extension `.r$`
2. Use filename to blob map to obtain the content for all versions of the R-language files obtained in Step 1
3. Analyze the resulting set of blobs to find a statement indicating an install or a use of a package:
   - `install.packages(\'\"PACKAGE\"\')`
   - `library(\'\"PACKAGE\"\')`
   - `require(\'\"PACKAGE\"\')`
4. Use blob to commit map to obtain all commits that produced these blobs and then use the commit to determine the date that the blob was created
5. Use commit to project map to gather all projects that installed the relevant set of packages

These steps are illustrated in a flowchart in Fig. 2. In Fig. 2 the rectangular boxes represent inputs and outputs, and ovals represent maps or dictionaries we utilized in this study. f2b stands for filename-To-blob map, b2cnt stands for blob-To-content map, b2cnt stands for blob-To-commit map, and cmt2prj for commit-To-project map. The number on the left side represents the unique number of corresponding objects.

A similar approach can be applied to other languages with suitable modification in the dependency extraction procedures, since different package managers or different languages might require alternative approaches to identify dependencies or the instances of use.

In addition to dependencies, we also need to obtain measures that describe various aspects of social relationships among developers because the theories of adoption, such as social contagion theory we employ, need measures of information flows among individuals as an important factor driving the rate of adoption.

### 3.3 Measuring the authorship network

The authorship network can be viewed as the process of developers working with other developers either by implicitly learning skills from other’s contribution (source code) or by explicitly communicating through emails or discussion platforms. Here we focus on the former mode of communication since the bulk of direct communication may be private. We consider two types of links among developers. A weak link exists between a pair of developers if they commit in at least one project that is common between them and a strong link exists if they change at least one file in common.

### 3.4 StackExchange

StackExchange is a popular question answer website related to programming. When people search for information there they may notice answers that suggest the use of either tidy or data.table (discussion about choosing these packages is in Sec. 3.7) and, consequently, might be inclined to incorporate one of these packages into their own code. The latest (2017-12-08) StackExchange data dump including 57GB of posts was imported into MongoDB, out of which 6k questions (excluding answers) were found to be related to either data.table or tidy by searching for these two terms in the title or the content of the post. We operationalize two measures: one counts the total number of posts.
while another measure counts only questions that have a score above 20 to gauge the amount of high-quality content that is likely to be referred to from search engines.

3.5 The Choice Model

The choice set (set of alternatives) needs to exhibit three characteristics to be able to fit a discrete choice model. First, the alternatives need to be mutually exclusive from the perspective of decision maker, i.e., choosing one alternative means not choosing any other alternative. Second, the choice set must be exhaustive meaning all alternatives need to be included. Third, the number of alternatives must be finite. The last two conditions can be easily met in our case: Our choice set consists of two packages - data.table and tidy; Decision makers are restricted into the group of projects in our collection where either of those two packages is installed. To ensure the choices are mutually exclusive we model the choice of the first technology selected.

In this paper we applied the mixed logit model to study developers’ choice over analogous R packages (data.table vs. tidy). While many variations of choice models exist, the mixed logit model has the fewest assumptions on the distribution of the choice. Here we are not trying to solve the classical choice model which, for example, assumes a complete knowledge about the alternatives and produces implicit utility function. Instead, we simply look for factors that strongly affect the decisions developers make, whether these factors may be rational or related to cognitive or social biases.

3.6 Issues

It's reasonable to believe that the number of issues and how an issue is solved during the development of a software package may affect a developer's choice. This factor belongs to a set of rational choices. To measure it we collect the issues reported during the development of data.table and tidy packages. Since both packages are hosted on GitHub, we use GitHub API to scrape all issues reported for both packages. We collected 2.6k issues for the data.table and 1.6k issues for the tidy.

3.7 Selecting candidates for study of adoption

We chose software technologies from the data science ecosystem of projects using the R language because several of the co-authors are knowledgeable and have decades of development experience in R, and we, therefore, do not need to seek external experts to provide interpretations of the findings. As with most language-based ecosystems, the core language provides only basic functionality with most of the external packages being maintained in CRAN and Bioconductor distributions. Each package can be thought as a technology package that is a part of core language provides not only the design philosophy, grammar, and data structures that are built for data science in R. Hadley Wickham, the Chief Scientist at RStudio and the main developer of tidy*, developed a family of packages called tidyverse to facilitate the usage of tidy* packages by assembling them into one meta package. We extract a set of packages from tidy* that share similar functionalities with data.table and refer to all of them here as the tidy package. This includes tidyr, tibble and readr packages.

data.table was written by Matt Dowle in 2008 and is known for its speed and the ability to handle large data sets. It’s an extension of base R’s dataframe package with syntax and feature enhancements for ease of use, convenience and programming speed. It’s built to be a comprehensive, efficient, self-contained package, to be fast in data manipulation, and it has a succinct DSL (domain-specific language). Conversely, tidy focuses on the beauty of function composition and data layer abstraction which enable users to pull data from different databases using the same syntax.

To analyze developers’ choice of these two packages, we collected and filtered relevant data by leveraging an open source mining infrastructure which provides not only APIs for extraction of development data on various levels for open source projects, but also intermediate collection-s/results extremely useful for study of domain knowledge. In particular, as illustrated in Fig. 2 and Sec. 3.2 we used the collection of all R file names and maps of file-to-blob, blob-to-content, blob-to-commit and commit-to-project to

3. A pull request is also treated as an issue in this paper. https://developer.github.com/v3/issues/

4. https://github.com/ssc-oscar/Analytics
discover our targeted projects. Meanwhile, for each project we found the first commit in which data.table or tidy was imported by sorting the commit time. By querying the content for this first commit, we came to know the author of this commit, commit message, etc. We set this first commit time as the end point of our analysis for each project, i.e., for every targeted project, we consider explanatory behavior, activities, and relationships as defined to be computed before this end point so that the analysis considers all factors as they were at the time of the analysis.

4.1 Operationalizing Attributes for Regression Models

In this section, we operationally define and justify the variables that quantify the key attributes pertaining to the set of software choices available to developers, as well as the characteristics of the developers making the choices.

We propose 11 variables to measure various aspects that may have influenced a developer’s choice. These variables are listed in Table 1.

- **Cmts & Aths** is the number of commits and author captures the size of a project which may affect package adoption. Larger projects, for example, may prefer less controversial/more conservative choices. This is a quality of the choice, so it would most closely fit under the “infectiousness” category in social contagion theory. We chose not to use lines of code (LOC) as size measure since it has less stable distribution than the number of commits, while, at the same time, being highly correlated with it. Operationally, for a particular adopter, we collected all commits prior to the end point (first adoption of one of 2 targeted packages) by applying project-to-commit map followed by a time point filtering. We extracted the authors of these commits and counted the unique number.

- **CumNum** is the overall number of project deployments (tidy or data.table) should increase the chance that a developer would be exposed to the usage of a package and may adopt it in their code. This measure falls within the “exposure” category of contagion, because it quantifies the chances that a developer may become aware of the technology. This is characterized as a factor that is not rational, as the project is hypothesized to be biased towards technology that they are more likely to encounter, not technology that would be optimal for that project. To assess CumNum for each targeted project at the time of potential adoption, we counted the number of adopter projects which had an earlier end point, i.e., the number of projects that already adopted a package (data.table or tidy) before a decision was made by the developers of package under evaluation.

- **Unsolved** issues can indicate package quality. A higher fraction of unresolved issues may indicate that the package has a significant number of problems, which, like a bad review, may undermine people’s confidence in it. This is a quality of the choice, so we hypothesize that it relates to the “infectiousness” aspect of the social contagion paradigm. To measure this quantity, we leveraged GitHub API to collect all issues for data.table and tidy packages and filtered issues raised before the decision end point for each adopting project. We count the number of unresolved issues and normalize it over all issues raised before end point, because in general a project tends to have more issues and unresolved ones as its age grows, and we believe the averaged rate of unresolved issues are more reflective of a package’s maintenance and quality.

- **C** code being associated with a project is used as a proxy for the requirement for high performance. Typically, computations that are too slow for the interpreted R language are implemented in C to improve performance. This is a requirement of the decision maker that would most closely fit under the “infectiousness” category because it likely indicates a strong preference for higher performance embodied by the data.table choice. This is a good example of a factor that may represent a rational choice for some decision makers. To measure this aspect, we applied commit-to-file map on every commit prior to end point for each project and filtered files with suffix ‘[cC]’.

- **StckExch** is a proxy for the popularity of each package. It counts the number of highly ranked (score > 20) questions related to each package. Developers often search for answers to issues they face and may stumble on one of these packages presented as a solution to a problem they are facing, thus increasing chances that they may adopt that technology. From the social contagion perspective this would increase “exposure”. We avoid counting the total number of questions because most of the questions tend to be of low quality and the search engines tend to avoid including links to them, thus they do not increase “exposure.” This factor may be interpreted from a rational perspective (leveraging experience of others when lacking other information), but more appropriately, it is a great example of social bias since the developer did not engage in due diligence, instead relying on social cues to make a technical choice. To measure this, we filtered related posts in the StackExchange dump (2017-12-08) by searching data.table and tidy in post title and content. Furthermore, we filtered posts with high quality by setting post score threshold as 20. Again, we counted posts raised prior to the end point for each adopter project.

- **Prx2DT/Prx2TD** measure dependency networks and can be understood from the perspective of software supply chain networks. Based on the characteristics of the software domain, especially the open source software community, dependency networks can be viewed as technologies (library/package) spreading from upstream (original package) to downstream (packages where the original package was installed) and, in turn, to further downstream packages.

We consider all downstream packages of data.table and tidy, e.g. those in the data.table and tidy clusters respectively. We hypothesize that if a project installed a package within the data.table cluster, then the project is more likely to install data.table than tidy. The rationale of such a hypothesis is that if developers installed a package because of 1)preference for some of its functionalities or features inherited from an upstream package or 2) the way such a package works, which is sometimes influenced by or derived from an upstream package, then it is more likely that these developers will gravitate toward the upstream package over other alternatives.

Based on the dependencies of R CRAN packages, the clusters of data.table and tidy are easily constructed.
the weights be based on several key principles:

- depth of package to network as S

We assume that each package has a weight of 1 in total. Let’s denote the packages set in the data.table as AD

Each downstream package in the data.table/tidy dependency network needs to be weighted before calculating proximity of an adopting package to both data.table and tidy. We suggest that the algorithm used to determine the weights be based on several key principles:

- for each downstream package, only the relative weight to the root package (data.table/tidy) matters
- for each downstream package, the sum of its weights to both root packages is a constant
- the closer to a root package, the higher the weight that a downstream package gets relative to that root package

We assume that each package has a weight of 1 in total. Let’s denote the packages set in the data.table downstream network as Sd, that in tidy as St, the weight of package a to data.table as Wad and that to tidy as Wat, the depth of package a in the data.table network as Dad and that in the tidy network as Dat, then based on principles mentioned above, the weights of package a are determined as follows:

- Wad = 1, Wat = 0 if a ∈ Sd & a /∈ St
- Wad = 0, Wat = 1 if a ∈ St & a /∈ Sd
- otherwise, Wad = Dat/(Dad + Dat), Wat = Dad/(Dad + Dat)

The next step is to extract the list of packages installed in each observation/project, after which we can aggregate the weights of these packages to compute the proximity of each project.

As we have mentioned in Sec.3.2 various maps among Git objects have been created. By utilizing maps of project-to-commit, commit-to-blob, and blob-to-content in sequence and selecting the install statements in blob content via regular expressions similar to those mentioned in Sec. 3.2, we get the list of packages installed in each project. From this set, we obtain projects that are either in data.table or in tidy clusters.

For a project p, denote the list of packages obtained in last step as Lp and denote a package in that list as a. Then the proximity of a project p to data.table, denoted as Ppd, and to tidy as Ppt, can be computed:

\[
\begin{align*}
P_{pd} &= \sum_{a \in L_p} W_{ad} \\
P_{pt} &= \sum_{a \in L_p} W_{at}
\end{align*}
\]

To summarize the process described above, we first measured the weight of each downstream package in either data.table or tidy by leveraging the R package dependency networks and the formulas above. Secondly, by following a similar flow in Fig. 2, we extracted all R packages that were adopted in the commits prior to end point where one of the focal packages was first adopted. Finally, we calculated the proximity to data.table and tidy by summing up the weights of all downstream packages for each project. Notice that a project’s downstream packages that were not in data.table or tidy downstream set were dropped.

AthPrx2DT/AthPrx2TD represents the proximity of a developer to a focal project as measured through their author network. It can be explained from the perspective of social contagion. Social contagion refers to the propensity for a certain behavior to be copied by others. Consider the fact that developers in GitHub are linked through common projects they are devoted to, where information and ideas are shared and transmitted from one to others, an underlying social network emerges. Organizational actions are deeply influenced by those of other referent entities within a given social system, according to DiMaggio [18]: non-adopters are influenced by adopters over time, and they influence the behavior of other non-adopters after their own adoption [11] if thinking of our case as package adoption.

In short, the adoption of data.table/tidy is a temporal process of social contagion.

We attempt to look for developers that are exposed to contagious packages — data.table/tidy. These developers include not only the authors of each package who are directly exposed inherently, but also developers who cooperate with directly-exposed authors in other projects. Authors of other projects that are directly exposed to authors of data.table/tidy, are identified by applying a project-to-author map to both data.table/tidy pack-

| TABLE 1: Independent variables |
|--------------------------------|
| **Independent variables** | Annotation | Category | Property type |
|--------------------------|------------|----------|---------------|
| CumNum                   | the total number of projects that deployed the package | exposure | choice related |
| RplGp                    | the time gap until the first reply to an issue | infection | choice related |
| Unrslvd                  | the number of open issues over the number of all issues | infection | choice related |
| StickExch                | the number of questions with score above 20 related to either package | exposure | choice related |
| C                        | boolean, indicating whether a project contains C file | proximity | decision maker |
| Cmts                     | the number of commits | proximity | decision maker |
| Aths                     | the number of authors/developers | proximity | decision maker |
| Prx2TD                   | the proximity to tidy through dependency network | proximity | decision maker |
| Prx2DT                   | the proximity to data.table through dependency network | proximity | decision maker |
| AthPrx2TD                | the proximity to tidy through authorship network | proximity | decision maker |
| AthPrx2DT                | the proximity to data.table through authorship network | proximity | decision maker |

| TABLE 2: Network characteristics |
|----------------------------------|
| **Characteristics** | **data.table** | **tidy** |
|----------------------|----------------|--------|
| # downstream packages | 813            | 2203   |
| # downstream layers  | 5              | 5      |
| # of packages in common | 636          |        |
| overlap ratio         | 0.78           | 0.28   |

More specifically, we used the METCRAN API and scraped meta data for more than 11 K R CRAN packages for which dependency information is available. Table 2 summarizes basic information on the networks that were constructed and more detailed information on the methodology follows.

In short, the adoption of data.table/tidy is a temporal process of social contagion.

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5. https://www.r-pkg.org/about
ages separately and indirectly-exposed authors are obtained by combining the map of author-To-project and the map of project-To-author serially and then applying it on each directly-exposed author.

We classify authors exposed to \texttt{data.table} into the \texttt{data.table} author cluster and those exposed to \texttt{tidy} into the \texttt{tidy} author cluster. Projects/observations may have authors who are in either of these two clusters and these authors may influence the choice of data frame technology, i.e., (\texttt{data.table} vs. \texttt{tidy}). In order to estimate the impact of every author in each cluster, we use the following weights,

\begin{itemize}
  \item \( W_{bd} = 1, \quad W_{bt} = 0 \) if \( b \in C_d \) & \( b \notin C_t \)
  \item \( W_{bd} = 0, \quad W_{bt} = 1 \) if \( b \in C_t \) & \( b \notin C_d \)
  \item otherwise, \( W_{bd} = D_{bt} / (D_{bd} + D_{bt}) \), \( W_{bt} = D_{bd} / (D_{bd} + D_{bt}) \)
\end{itemize}

where \( b \) represents an author in a project; \( C_d/C_t \) stands for author cluster of \texttt{data.table/tidy}; \( D_{bd}/D_{bt} \) refers to the distances from author \( b \) to \texttt{data.table/tidy}, i.e., author \( b \)'s depths in the author cluster of \texttt{data.table/tidy}, 1 for directly-exposed author and 2 for indirectly-exposed author; \( W_{bd}/W_{bt} \) is the proximity of author \( b \) to \texttt{data.table/tidy}, indicating author \( b \)'s impact on choosing \texttt{data.table/tidy}. Note that these measures are similar to the ones used in calculating \( P_{x2DT}/P_{x2TD} \) and are based on similar principles.

After estimating each exposed author’s influence, the overall exposed authors’ influence in project \( p \) can be measured as follows:

\[
PA_{pd} = \frac{\sum b A_p W_{bd}}{N_p} \\
PA_{pt} = \frac{\sum b A_p W_{bt}}{N_p} 
\]

(2)

where \( A_p \) is the set of authors of project \( p \) who are in either of \texttt{data.table/tidy} author cluster; \( W_{bd}/W_{bt} \) is the proximity of author \( b \) to \texttt{data.table/tidy} calculated in previous step; \( N_p \) is the number of authors in project \( p \); \( PA_{pd}/PA_{pt} \), i.e., \( AthPrx2DT/AthPrx2TD \), is the overall influence of exposed authors on a project \( p \). Notice that \( AthPrx2DT/AthPrx2TD \) is calculated through aggregating the influence of each exposed author and being normalized over the total number of authors in that project. The rationale for normalization is that a project tends to have more exposed authors if it contains more authors, resulting in a higher value for \( AthPrx2DT/AthPrx2TD \). By normalization we remove this bias induced by the difference in the number of authors for different projects. This factor falls clearly within a realm of a social bias. It may also be partially explained as cognitive bias if the developer is not aware of alternative choices.

To summarize the computation of proximity through authorship network, we started by measuring the weight of each author who was either a co-author of \texttt{data.table/tidy} or had cooperated with at least one of the authors of \texttt{data.table/tidy}, which was detailed above. Then we summed up the weight of every author of a project and normalized it over the total number of authors in this project. Again, here we applied end point filter on every step in calculation.

\( \text{RplGp} \) measures how fast the developers or maintainers of a package respond once an issue has been raised. The timeliness of this response reflects the efficiency of package maintenance and can be attributed to the ‘infectiousness’ category of social contagion theory and could clearly be of interest for those deciding on which package to adopt. The calculation of reply gap is worth discussing. We are interested in understanding how long it takes for an issue to get its first reply after being reported. For each individual in the study, we focus on the time period just before the key commit that includes the choice of focal package (\texttt{data.table/tidy}). However, several additional obstacles that needed to be addressed in order to measure the reply gap:

1. It is rare that an issue was raised simultaneously with the key commit (inside which either the \texttt{data.table/tidy} package is installed).
2. The timeliness of replying to an issue may vary drastically during the development of a package, hence taking the closest issue’s reply-time as a representative is not reasonable
3. For some issues, it took a significant amount of time to get a reply and in some cases no reply was ever made to an issue, thus, averaging reply-time to previous issues is problematic due to long right-censored cases.

This is a case where statistical models for survival (time-to-event) are appropriate. In this scenario, an issue can be viewed like a patient under study with the first reply analogous to conclusion of the medical issue or death of the patient. We aim to model the time until reply to the reported issue, i.e., the survival time of the issue, with shorter lifetimes indicating a more interactive development team. Irrespective of package, for each issue, we record the time that it was submitted (timestamp recorded when the issue is raised) and use survival analysis to model the distribution of the issue lifetimes for each package (\texttt{data.table/tidy}) using the R package ‘survival’ [41]. Predictions for the reply time for each project (observation) can be made based on data collected before the key commit. The \( \text{RplGp} \) for a project is simply the median issue lifetime for an issue generated before a key commit. This factor appears to be clearly related to rational choice factors as the delays in response may cause real problems.

In practice, we extracted all issues of \texttt{data.table/tidy} from GitHub and measured difference between the time an issue is first raised and the first response time. As described above, we trained a survival model to estimate the distribution of the delay until first response. The model was trained using all issues that had been raised before the current package key commit. Those issues that had not been responded to yet were right censored in the model fitting. The reply gap represents the median value of response times.

In summary, we note that for each project that eventually adopts one of the two focal packages (\texttt{data.table/tidy}), all of the variables described in this section are calculated dynamically using only data that occurs before the key commit. In addition, for each observation, every predictor with choice property (Table 1) needs to be calculated for
both packages, e.g., Unrslvd needs to be calculated for both data.table and tidy. These will end up being denoted as Unrslvd.data.table and Unrslvd.tidy.

5 Results

We identified 24,000 projects (7,000 for tidy, 17,000 for data.table) that installed either data.table or tidy between June, 2009 and January, 2018. After removing forks, we were left with a total of 8,000 projects (3,000 for tidy, 5,000 for data.table). Furthermore, we removed project adopters occurring prior to June 16, 2014, when tidy was first introduced. Before then and only data.table existed as a viable option, so no choice was possible. As a result, we dropped approximately 20% of 5,000 data.table observations representing adoptions prior to June 16, 2014. The remaining projects serve as observations in our choice model. Table 3 summarizes basic statistics for independent variables analyzed in the model. We use the R package ‘mlogit’ to fit the model using the 11 predictor variables defined above with the response being an indicator of the package chosen.

Very high correlations among predictors (above 0.9) occurred between Prx2DT and Prx2TD. High correlations may lead to unstable and difficult to interpret models and need to be addressed. Since we do not have any a priori theory-derived reasoning for removing one or the other variable, we removed Prx2DT. The modeling results remain stable if this approach is reversed. Table 4 presents the resulting model fit.

TABLE 3: Summary Statistics for Independent variables

| Variable          | median | mean  | std.dev |
|-------------------|--------|-------|---------|
| Cmts              | 3      | 46.83 | 645.68  |
| Aths              | 1      | 2.13  | 8.23    |
| C (boolean)       | 0      | 9.79e-03 | 9.85e-02 |
| Prx2DT            | 0      | 0.15  | 0.95    |
| Prx2TD            | 0      | 0.62  | 2.79    |
| AthPrx2DT         | 0      | 6.99e-2 | 0.17   |
| AthPrx2TD         | 0      | 0.11  | 0.24    |
| CumNum.data.table | 2.72e+03 | 2.66e+03 | 1.87e+03 |
| CumNum.tidy       | 305    | 8.44e+02 | 9.12e+02 |
| RplGp.data.table  | 1.41   | 1.42  | 0.21    |
| RplGp.tidy        | 1.95   | 1.98  | 0.31    |
| Unrsld.data.table | 0.27   | 0.25  | 4.00e-2 |
| Unrsld.tidy       | 0.15   | 0.19  | 7.46e-2 |
| StckExch.data.table | 130    | 125.76 | 6.53    |
| StckExch.tidy     | 158    | 152.57 | 10.14   |

Below we summarize findings for each predictor variable separately.

StckExch: the coefficient is 0.2, indicates that the number of high quality questions on StackExchange is associated with the likelihood that a project would adopt the respective technology. The association is positive, holding other factors equal. For illustration, if the number of high quality questions increases by 6 questions (1 std. dev.) from a median value of 130 for data.table, the estimated probability of choosing data.table increases from 0.58 to 0.87, while holding all other predictors at their median values.

This result aligns well with the social contagion theory that posits that increased adoption is a consequence of increased exposure. Surprisingly, including an additional predictor that counts the total number of questions (of high and low quality), shows no statistical significance. It appears to be counter-intuitive as more exposure should increase adoption. However, when developers want to solve an issue related to the functionality of the R data.frame, they often may not search on StackExchange, but use a general search engine and follow links to StackExchange. The total number of posts, therefore, may be not visible to developers, only the set of posts that the search engine deems to be of sufficiently high quality. The number of posts (questions), may, therefore, not be a good proxy of exposure. As such, the total number of posts of Low-quality questions, in fact, appear to discourage developers from using a package.

TABLE 4: The Fitted Coefficients.

| Variable          | Estimate | Std. Error | p-val |
|-------------------|----------|------------|-------|
| tidy:(intercept)  | -6.72    | 0.26       | 2.20e-16 |
| CumNum            | 1.43e-04 | 1.43e-05   | 2.20e-16 |
| Unrsldv           | 8.30e-02 | 0.72       | 0.91   |
| RplGp             | -0.33    | 7.94e-02   | 2.52e-08 |
| StckExch          | 0.25     | 0.01       | 2.20e-16 |
| tidy:Cmts         | -4.63e-04 | 2.26e-04 | 5.64e-2 |
| tidy:AthPrx2TD    | 8.53e-05 | 7.17e-03   | 0.99   |
| tidy:C            | -0.64    | 0.28       | 2.40e-3 |
| tidy:Prx2TD       | 0.18     | 2.89e-02   | 6.78e-10 |
| tidy:AthPrx2TD    | 1.27     | 0.14       | 2.20e-16 |
| tidy:AthPrx2DT    | -9.03e-02 | 0.19     | 0.65    |

Finding 1: We found that exposure measured via the total number of questions on StackExchange had no impact on adoption, while the number of high quality questions has a strong and positive correlation with increased adoption.

Finding 2: We did not find statistically significant association between infectiousness as measured via the fraction of unresolved issues and adoption rates

Unrsldv: the ratio of unresolved issues over total number of issues does not show a statistically significant association with the choice between the two technologies. This might be due to the fact that the ratio of unresolved issues can not be easily observed by adopters, e.g. the default number in the issues tab on GitHub represents the current number of issues that are not resolved and adopters have to take a further step to calculate such ratio. Another explanation is that adopters may investigate influential unresolved issues instead of all unresolved issues, which suggests that more detailed issues analysis such as segmentation and classification are required to understand adopters’ decision making process more precisely.

AthPrx2TD: the coefficient is 1.3, indicating that the closer a project is to authors of the package tidy vis-a-vis the author network, the more likely they are to choose tidy over data.table. If the proximity to tidy in the author network increases by one standard deviation of 0.24 from a median value of 0 (e.g., a project that has four authors and one of them cooperates with tidy’s developers, but not with any of data.table’s developers), the estimated

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6. https://cran.r-project.org/web/packages/mlogit/vignettes/mlogit.pdf
probability of choosing tidy increases seven percent from 0.42 to 0.49. This finding supports the basic premise of the social contagion hypothesis that developers’ choices are affected by the environment they are in.

Finding 3: Proximity as measured by the fraction of authors who are either developers of the package to be adopted or who work with at least one developer of that package, increase the chances of adoption.

This may be a consequence of authors who have direct experience or are familiar through word-of-mouth. However, AthPrx2DT is not statistically significant. One reason may be that data.table is a more widely deployed package and the deployments may play a larger role than the social connections. Also, each community of users and developers may be different. For example, the tidy community may have more social interactions than the data.table community. Furthermore, the exposure in the tidy community may come from a much larger set of packages in the tidyverse, while data.table does not have an equivalent brand that involves a wider variety of tools beyond data handling.

C: the coefficient is -0.6, indicating that a project containing at least one C file is less likely to choose tidy. The estimated chances of choosing data.table increase by 15 percent from 0.58 to 0.73. The finding is consistent with our hypothesis that if an R project has a need for performance, as evidenced by the use of functionality being developed natively in C language, then it is more likely to choose the higher performance of data.table.

Finding 4: Proximity, as measured by the project’s need for performance, is associated with adoption of packages that emphasize high performance

RplGp: the coefficient is around -0.4, indicating that the more quickly a package’s issue gets a response, the more likely that this package will be chosen. If the number of days until first response to an issue increases by 0.21 days (1 std. dev.) from a median value of 1.4 for data.table, the estimated chances of a project choosing data.table decrease by two percent from 0.58 to 0.56 assuming all other variables remain at their median values. The time until first response is not as readily visible to developers as most other measures that we used, so developers may not be able to observe it when making a choice. However, it appears to be a reasonable proxy for project’s reactions to external requests that could be easily gleaned by reading through some of issues on the issue tracker. A well maintained package is more likely to respond to new issues quickly and thoroughly, leaving a good impression and, thus, increasing the likelihood of being adopted. This has implications for designing project dashboards intended to make key project attributes more visible.

Finding 5: Infectiousness of a package as measured by speed of response to issues is associated with a higher adoption rate for that package.

Prx2TD: the coefficient is 0.2, indicating that the closer (through a dependency network) a project is to the package tidy, the more likely its authors are to choose tidy over data.table. If proximity to tidy in dependency network increases by one standard deviation of 2.8 from a median value of 0 (e.g., a project installs/uses three packages that are in first layer downstream from tidy), the chances of choosing tidy go up by 12 percent from 0.42 to 0.54. It supports our hypothesis that the supply chain influences projects’ choices. A project tends to install a specific package if it has already installed other packages that also depend on it, i.e., if a project uses downstream dependencies of a package, it is more likely to use the package itself rather than other alternatives. Being familiar with downstream packages may reduce the overhead or learning curve required for an upstream package, leading to an advantage over other choices.

CumNum: the coefficient is 1.4e-4, indicating that a larger number of deployments of a package in the past will make it more likely to be adopted. If the number of deployments increases by one standard deviation, 1870 projects, from a median value of 2660 projects for data.table, the estimated chances of choosing data.table go up by seven percent from 0.58 to 0.65 for a project holding all other values at the median. A larger number of overall deployments, on one hand, increases the chance for a package to be known by adopters. On the other hand, from the perspective of adopters, more deployments usually insinuate a stable and mature product (though it is not clear if the number of deployments is visible to a developer), and enhances adopters’ confidence in this package. Either of these reasons justifies adoption of the widely deployed package as predicted by the social contagion theory.

Finding 6: Proximity to a package as measured via technical dependency networks is associated with a higher adoption rate.

Finding 7: Exposure to a package that is widely deployed is associated with a higher adoption rate.

Finding 8: We did not find statistically significant association between infectiousness as measured via the number of commits and adoption propensity.

a. the coefficient is not statistically significant at 0.005 level recommended for reproducibility; see Table 4 and 43.

We also find that the number of authors in the adopting project does not affect the choice of technologies. Social contagion theory does not suggest that this predictor should have an effect, but it could be that project activity (which has a substantial correlation with the number of authors), may already account for the differences in propensity to chose tidy over data.table making the variation in the number of authors statistically insignificant. We achieved a McFaddens pseudo-$R^2$ of 0.14, which is a good fit according
to McFadden [22]. (Notice that the R package ‘mlogit’ use McFadden $R^2$ instead of $R^2$ to estimate fitness of the model because logit models don’t generate the sums-of-squares needed for standard $R^2$ calculation.)

Regression models are explanatory, but we can also use them to do prediction. The 10-fold cross-validation done by randomly splitting projects into 10 parts and fitting the model with predictors listed in Table 4 on nine parts and predicting on the remaining part yielded a reasonable AUC of 73%. Average accuracy was 70% with balanced Type I and II errors (obtained by choosing predicted probability cutoff of 0.49).

Finally, it is worth noting that out of six predictors that were statistically significant, only CumNum, RplGp, and C were clearly grouped into predictors that would support rational choice. The remaining three predictors primarily reflect a mixture of social and cognitive biases associated with social preference or default choice when alternatives are not known. If we include the effort needed to obtain the necessary information into the utility function, these social and cognitive biases can, of course, be explained rationally as well.

In a parallel study to the regression analysis discussed above, surveys were emailed to 1085 of the developers that had committed R projects containing the data.table and tidy libraries. The purpose of the 12-question survey was to gain insights into the reasons behind the user’s selection of a particular package. One of the survey questions asked the 803 respondents how important 13 common factors were when selecting a package to expand the function of the basic R data.frame. Respondents selected a factor-tile, such as “Package’s Historic Reputation”, and moved it to the box that represented the priority for that user. A user could select/drag as many or as few tiles as they wanted.

In agreement with the presented regression, both data.table and tidy users indicated that they value Stack Exchange as a technical reference. tidy users place importance on the reputation of the author and the package, reinforcing the sentiment associated with the significant regression variables Prx2TD and AthPrx2TD. The data.table users are concerned with computing performance, bolstering the regression findings that a project with at least one C file is likely to choose data.table. (Note: The shortened labels below correspond to the order of the tiles above. The full summary of the survey results can be found by following the hyperlink listed after Section 8)

6 LIMITATIONS

Empirical studies must be interpreted carefully due to a number of inherent limitations. Here we highlight some of the potential issues and how we tried to address them.

To obtain an unbiased picture of technology spread representing the entirety of the projects, we consider a very large collection of projects. While large, our sample cannot be complete as many projects do not publish their code and our collection may have missed even some of the public projects. The sample we have should limit the findings to projects that share their version control data on one of the many forges, such as GitHub, BitBucket, GitLab, Bioconductor, SourceForge, etc. However, it may not be representative of the entire universe of projects, especially projects that do not publish their version control data.

We have selected only projects with extension [rR] but some older projects may use extension [sS] indicating the historic name for R language, or some other source code without any (known) extension.

Regular expressions that we used to identify instances of package usage or installation can capture most of the install statement in the .r/R file, however, in some cases the install statement may be missed due to a dynamic specification in the installation such as in the case below,

```
ipak <- function(pkg){
  new.pkg <- pkg[!(pkg %in% installed.packages()[, "Package")])
  if (length(new.pkg)) install.packages(new.pkg, dependencies = TRUE)
  sapply(pkg, require, character.only = TRUE)
}

# usage
packages <- c("ggplot2", "plyr", "reshape2", "RColorBrewer", "scales", "grid")
```

Fig. 3: Survey Question 5

Fig. 4: Survey Question 5 Summary
Moreover, regular expressions may falsely capture an install statement in some cases, e.g., install statements that are commented out may, in rare cases, be captured by regular expressions. Files that are contained in a project but not used may also contain install statements that are captured by regular expressions. To alleviate this issue we used the R language requirement to have a comment character ‘#’ on each line and ensured that the matched install is never preceded by the comment character.

These potential errors would affect the dependency networks we construct and result in an under/over-count of the number of packages used by the packages we are looking for. Developer identities may not be spelled the same way and that may affect the author network [43]. We have tried to address these and other issues encountered when dealing with operational data from software repositories and big data [45], [46], [47].

In order to validate our findings in domains other than R, we applied our model and approach on JavaScript frameworks (Angular, React) and achieved similar results [4]. We expect that more cases will be studied in the future testing external generalizability of this approach.

It is important to note that the particular operationalizations of the concepts from social contagion theory are just a few of the possibilities. Measures are not entirely orthogonal: each measure may capture the aspects of other dimensions beyond the one it is intended to measure. The correlations among predictors may lead to unstable models that are hard to interpret. We address this limitation by carefully considering various interpretations of the measures, conducting exploratory analysis of the obtained measures, selecting a subset that does not pose threats to model stability and investigating compliance with model assumptions including inspection of outliers, non-homogeneous variance, and performing general model diagnostics. We also model the first choice, but it is also reasonable to model the full set of choices made. In the latter case, we need to include the third option, i.e., projects choosing both packages: tidy and data.table. We fitted a variety of alternatives to ensure that the reported results are not affected by these variations in the approach. We only present the results for two alternatives due to space considerations, but we have applied choice model on several other R packages as well.

Finally, here we demonstrate how to use the social contagion modeling using version control data to evaluate developer behaviour when choosing software packages. The particular results we obtained for R and the specific two packages may not, therefore generalize beyond this specific context. Only additional studies in multiple contexts can validate the generality of these findings.

7 RELATED WORK

The closest related work involves studies of use and migration of software libraries. A number of metrics and approaches were proposed to mine and explore usage and migration trends. A software library encapsulates certain functionality that is then used by applications (or other libraries). The application may benefit from extra functionality or performance in the new libraries that may be created later, but switching to a new library (library migration) involves some recoding of the application [48], [49], [50], [51], [52]. Most prior work, therefore, focused on costs and benefits of library migration [53], [54], [55], [56], [57], [58], [59], [60]. Similarly to that work we ask why developers chose a new library. In contrast to prior work, we construct new predictors of adoption (e.g., technical and author dependency networks, breadth of deployment, quality of support measured through StackExchange, issue number and response times) that are based on sound theoretical foundations and we use choice models to understand how macro trends at the scale of the entire SSC emerge from actual decisions the individual developers make to select a specific software technology.

Approaches to detect library usage include issue report analysis [53]. As in prior work we detect usage by searching for library statements in source files of projects [54]. De la Mora et al. [55] introduce an interface to help developers choose among the libraries by displaying their popularity, release frequency, and recency. While building on this research, we add novel network, deployment, and quality measures that would inform developer choice. More importantly, we radically improve the ability of developers to make informed decisions by providing a statistical model that explains which of these measures matter and how they affect the choice.

Prior studies that examined technology choices have used a variety of approaches ranging from surveying developer preferences [61] and reasons [62] behind, to mining version control and issue tracking repositories [53], [54], [55]. Similarly, we mine version control data, but at a larger scale of all projects with public version control data that include R language files. This allows us to construct complete software supply chains that depict end-to-end technical and social dependencies.

8 CONCLUSIONS

Integrating software supply chain concepts and models to operationalize key variables from social contagion theory to investigate software technology adoption appears to have provided a number of potentially useful insights in the present case study of two data manipulation technologies within R language. More specifically, the methodology was able to identify factors that were influential in decision-makers’ choices between software technologies and demonstrate the need to account, not only for the properties of the choice, but also of the chooser and of the importance of the supply chain dependencies and information flows. It also validates the measures deemed to be the drivers of technology adoption by the social contagion theory.

This study introduces the concept of two types of software supply chains (based on technical dependencies and...
on the relationships among developers induced by projects they have worked on) and demonstrates how software supply chains for the entire open source ecosystem can be reconstructed as they have existed at any point in the past from public version control systems. Additionally, by taking a social contagion perspective and employing the logistic regression models, we explicate a parsimonious model that is capable of modeling software technology choices. The findings of this study have wide reaching implications for the software engineering community as well as those who study traditional supply chains. For example, the ability to model and understand which aspects of a network of software supply chain partners and affiliates influence uptake and spread of a given artifact (e.g., package or product) might help contributors adjust their contributions in a way to maximize their reach, while also extending the viability and propagation of a core package or product. This notion is consistent with our findings that a number of characteristics of a developer and properties of technology are found to be important in the choice between major alternatives. More specifically, packages with large number of overall adopters, higher responsiveness to new issues, and more high-quality stack exchange questions are more likely to be chosen. Furthermore, from the perspective of a project’s decision-makers, their technical features and proximity to a technology in both the technical dependency network and author collaboration network increase the probability of adoption. On a more speculative side, we find that half of the significant predictors do not appear to be related to a traditional rational choice, but are likely a reflection of social and cognitive biases or, in plain language, shortcuts people take. Developers, at least in the context of technical decisions regarding which package to use, do not appear to be immune from these biases.

Source code and data for this study is publicly available to facilitate reproducibility and wider adoption of the proposed methodology.

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