Modeling the Impact of R & Python Packages: Dependency and Contributor Networks

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Introduction

- **Open Source Software (OSS)** is a computer software with its source code made available with a license in which the copyright holder provides the rights to *study, change, and distribute* the software to anyone and *for any purpose* [Open Source Initiative, 1998].
  - within and outside of the private sector
  - universities (e.g., Stanford, MIT, UC-Berkeley), business (e.g., Microsoft, Google), government research institutions (e.g., Sandia National Lab), nonprofits, and individuals
- Examples include Linux, Apache, Python, and R.


- Public funding for OSS is not fully accounted!

Introduction

Ways to Measure the Scope and Impact of Open Source Software

- Cost of Software Package Creation
  - Identify number of people involved each package's development;
  - Estimate time spent on software development;
  - Use average compensation for computer programmers;
  - Estimate intermediate inputs based on BEA (Bureau Economic Analysis) and OECD (Organisation for Economic Co-operation and Development) methodologies.

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*The National Bureau of Economic Research (NBER) Conference: Big Data for 21st Century Economics. Bethesda, March 2019.

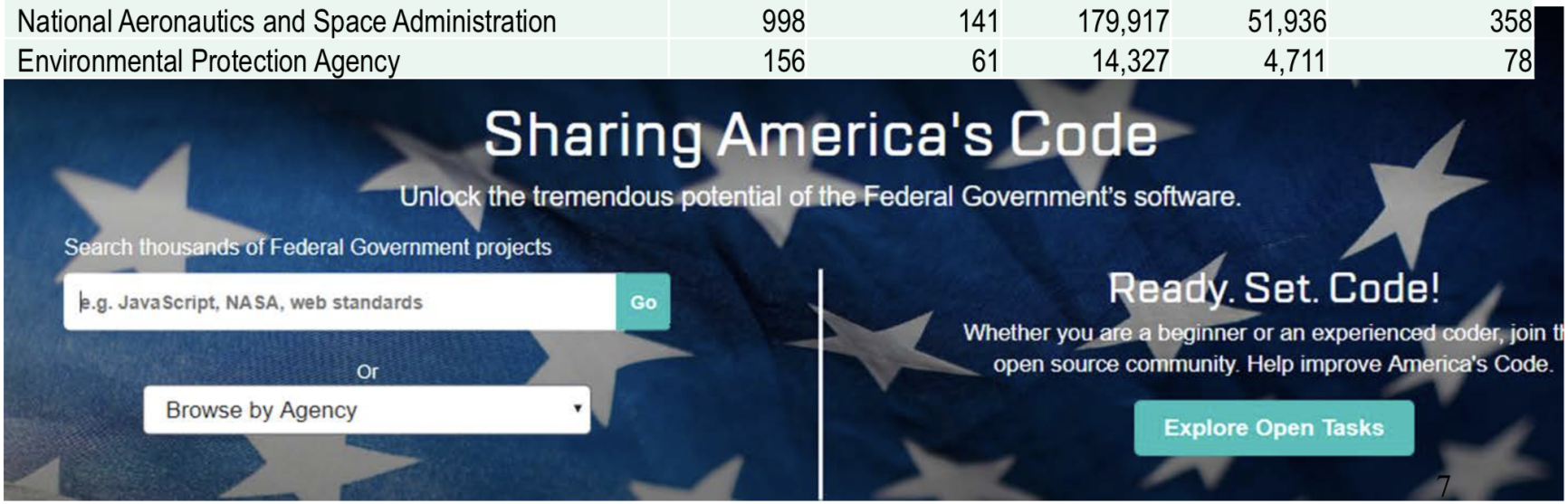
*International Monetary Fund (IMF) Statistical Forum on Measuring Economic Welfare in the Digital Age: What and How? Washington D.C., Nov. 2018.

*The International Association for Research in Income and Wealth (IARIW): The Digital Economy: Conceptual and Measurement Issues. Copenhagen, Aug. 2018.

OSS in Federal Government

Open Source Projects by Federal Government Organization
Top 5 by number of projects
for projects started before January 1, 2018

Organization Name	Total Projects on Code.gov	Number of Projects Linked to Github collection	Kilo-lines of code (kloc)	Commits	Number of contributors
Total	4,457	2,688	2,486,210	950,625	8,292
General Services Administration	1,501	1,368	266,860	318,676	4,631
Department of Energy	899	704	1,219,835	485,726	2,433
Consumer Financial Protection Bureau	261	243	753,447	49,781	334
National Aeronautics and Space Administration	998	141	179,917	51,936	358
Environmental Protection Agency	156	61	14,327	4,711	78



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Resource Cost Based on GitHub Data

- Methods used in software engineering
- Based on lines of code, effort, and man-hours

Package Name	KLOC	Estimated Cost in Thousands of 2017$
All packages	282,167.871	883,209
archivist	28488.639	4,169
CollessLike	15844.721	3,299
readtext	13888.309	3,130
ptwikiwords	11452.965	2,898
nasapower	10613.638	2,812

Package Name	KLOC	Estimated Cost in Thousands of 2017$
All packages	611,601.568	1,560,374
libsass	50340.53	5,233
py3-ortools	37412.424	4,648
LSD-Bubble	15270.398	3,251
IotPy	14899.252	3,219
openquake. engine	13841.578	3,126

- Refinement needed!

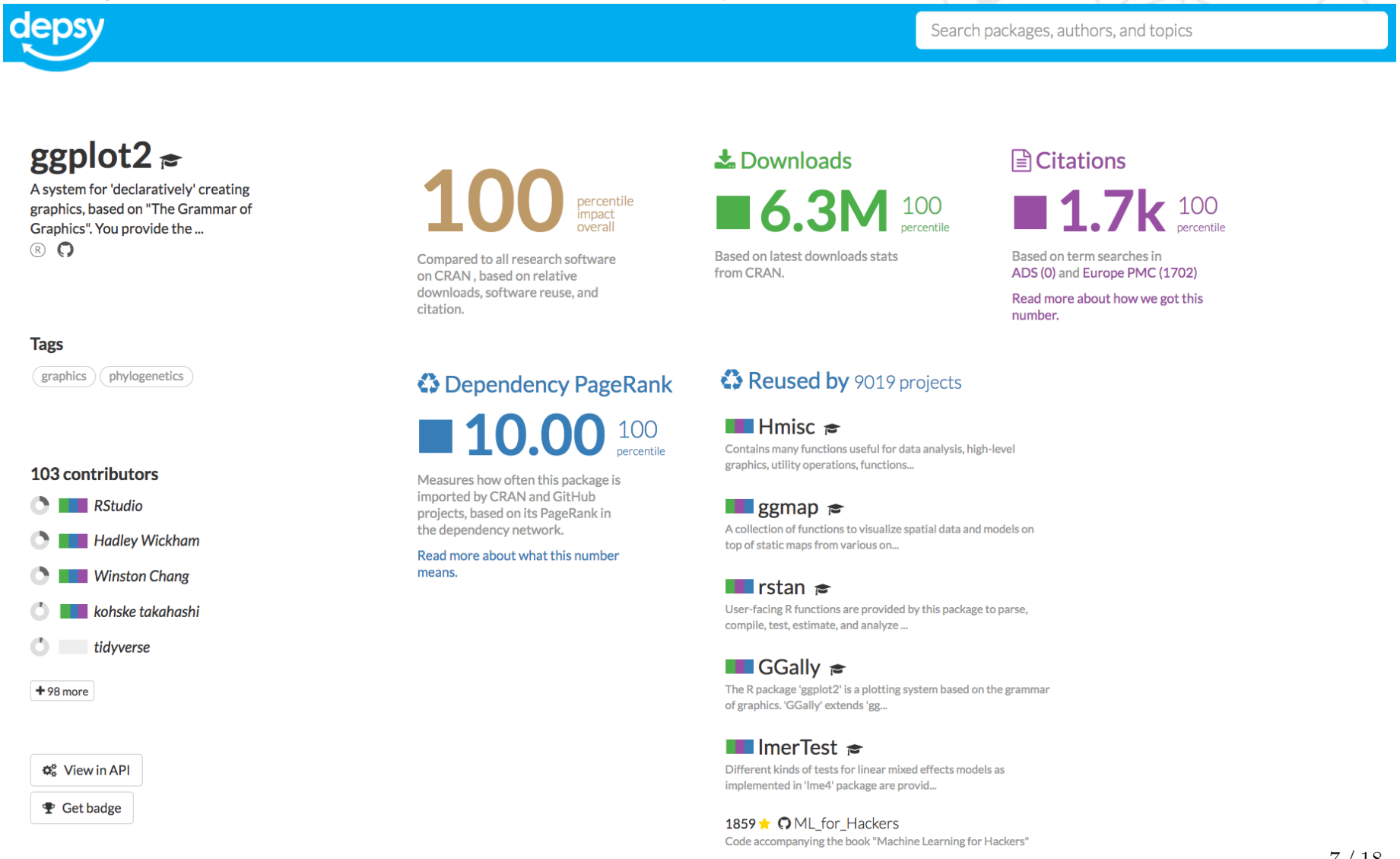
In this paper...

- Focus on **relative package impact (value)** of R and Python packages using methods from bibliometrics and patents
  - Counts
  - Downloads
  - Citations
  - Reuse in other packages (dependencies)
- Goal is to identify the factors that affect the impact, measured by **downloads and citations**
- Collect publicly available information on R and Python packages
- Generate **dependency and contributor networks** of OSS "ecosystem"
- Develop statistical models to estimate the impact using
  - structural properties of the dependency and contributor networks.
  - author and package attributes

*Preliminary version appeared in *Proceedings of the 2018 IEEE/ACM International Conference on Advances in Social Network Analysis and Mining (ASONAM)*. pp. 511-514. IEEE.

Data Source

Depsy.org: a website that compiles R and Python packages to quantify coding *impact* in the scientific community.



Data Collection

- **R**
  - Gathered all of the R packages listed on CRAN: 10,926 packages
  - Scraped the characteristics from the JSON page affiliated with each R package from Depsy
  - Information about 9.8K packages and around 14K affiliated contributors
- **Python**
  - Gathered all of the Python packages listed on PyPI: 192,666 packages
  - 43K Python packages and around 48K affiliated contributors

Contributor Name	Number of Python Packages
Plone Collective	495
ube	419
Amalgam8 Team	352
Contributors	288
Marc Abramowitz	288
Total: 48,255 Contributors	

Contributor Name	Number of R Packages
Hadley Wickham	104
Scott Chamberlain	87
rOpenSci	74
Dirk Eddelbuettel	64
RStudio	61
Total: 13,883 Contributors	

Analysis

- Impact measures: citations and downloads.

Distributions of Downloads and Citations for Python and R

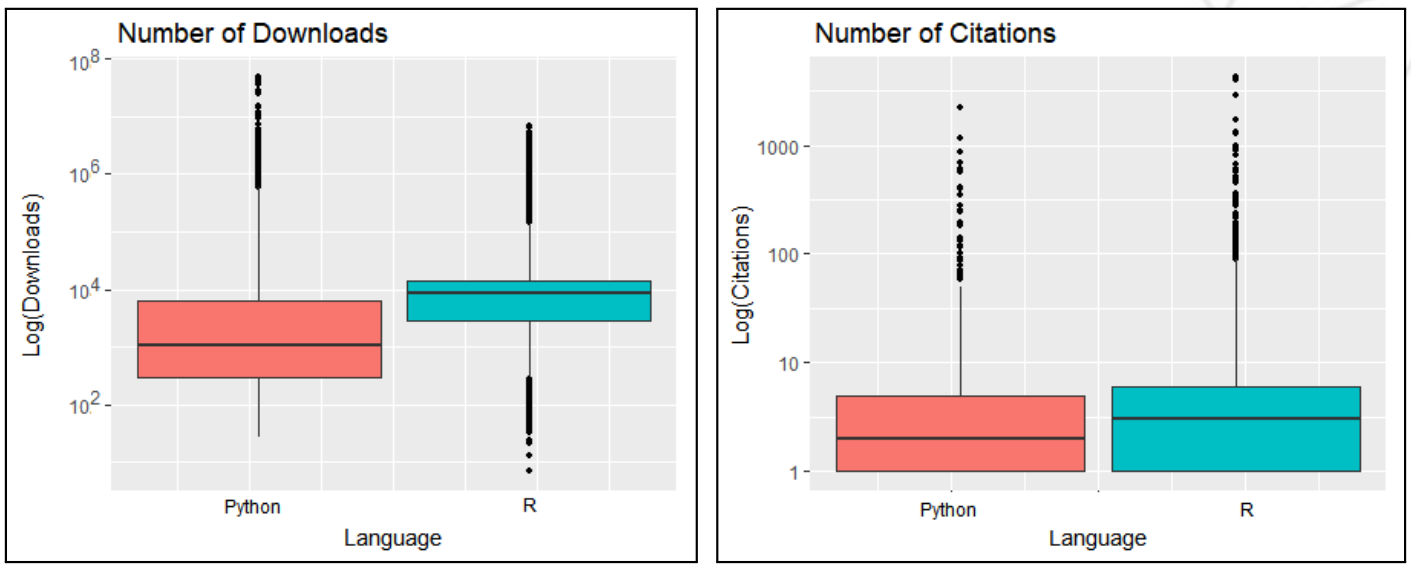


Figure: Histograms and boxplots of number of citations (left) and number of downloads (right) for Python and R packages. Both of these metrics are right-skewed.

Analysis

Top Downloaded Packages	Number of Downloads	Top Cited Packages	Number of Citations
Rcpp	6,683,565	vegan	4,275
ggplot2	6,255,500	lme4	4,023
stringr	5,366,703	nlme	2,916
plyr	5,345,308	ggplot2	1,702
digest	5,251,824	gplots	1,307

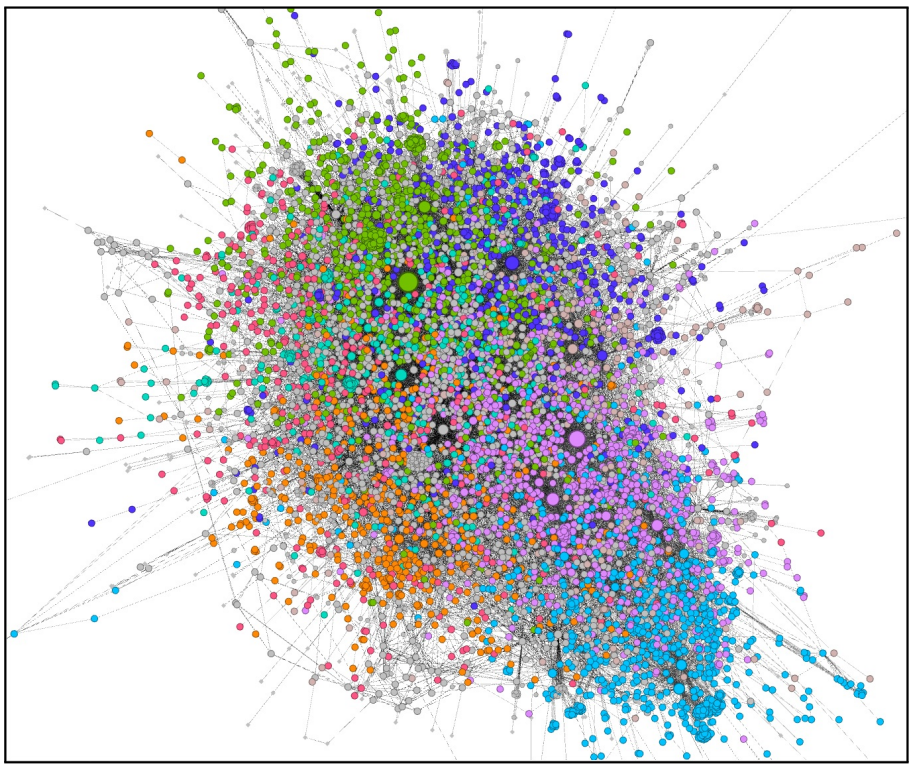
Table: **Top Downloaded and Cited Packages in R**

Dependency Network

- $i \rightarrow j$ indicates that the package j requires i to function

Table: **Structural Features of the Dependency Networks**

	Nodes	Edges	Avg. Degree	Diameter	Avg. Clustering Coefficient	Avg. Path Length	Connected Components
R	7,389	20,235	2.74	9	0.07	2.4	56
Python	168,921	545,186	3.23	22	0.07	7.8	174



Dependency Network of R Packages

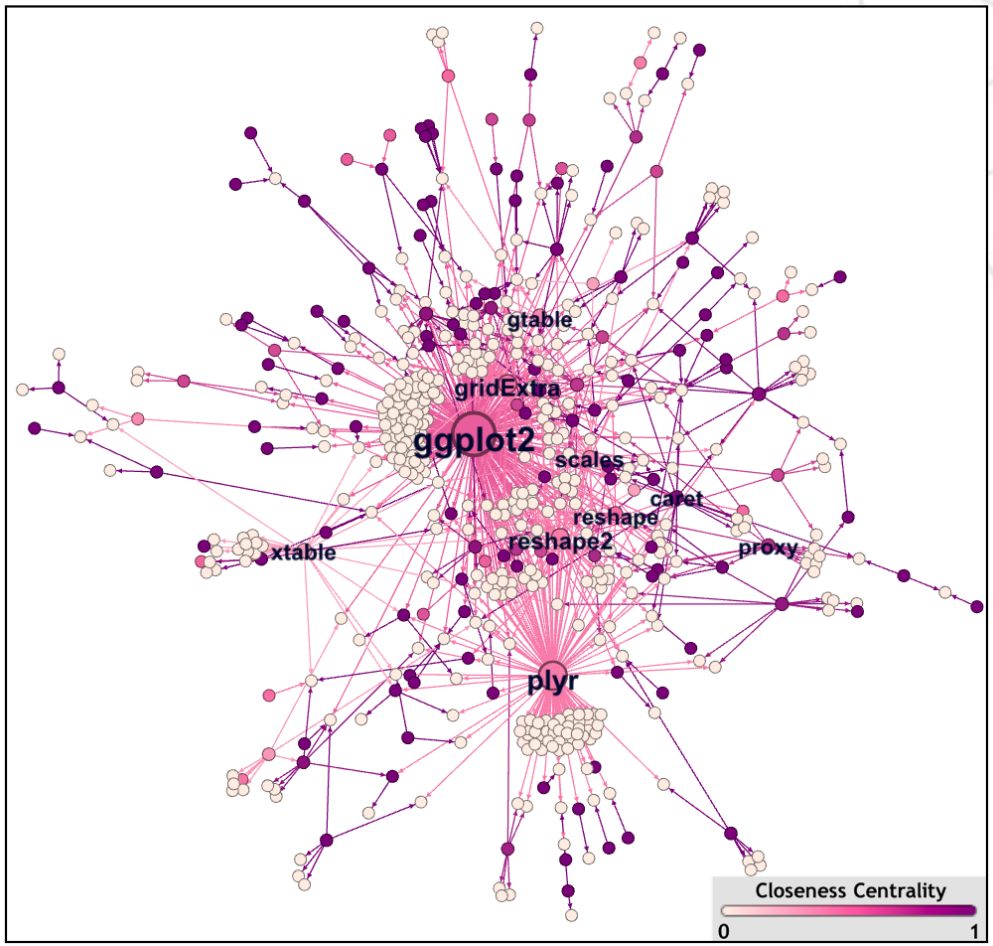


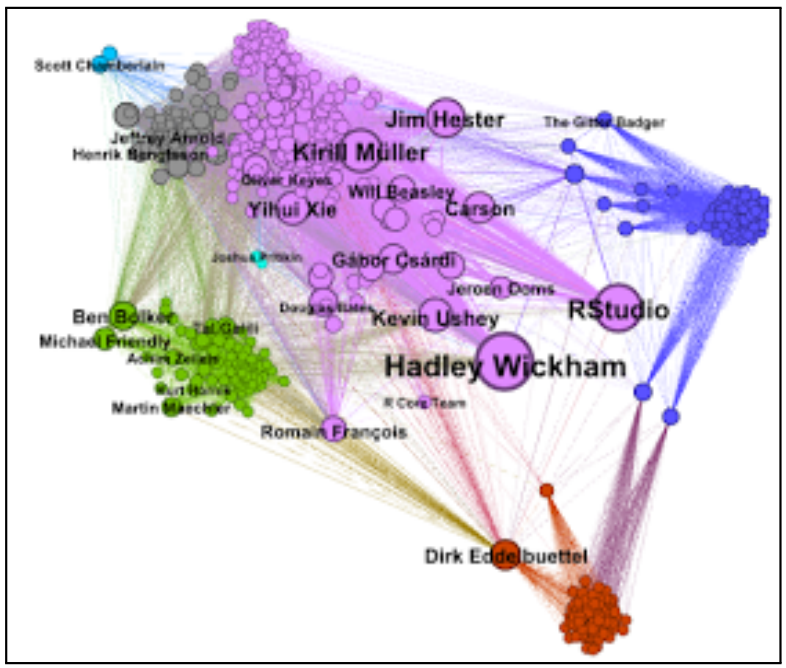
Figure: A subgraph of the dependency network of R packages on Depsy that includes 572 nodes (7.74%). The size of the node indicates the outdegree (the top nodes are labeled), and the color represents the closeness centrality.

Contributor Network

- An undirected edge between i and j indicates that user i and j contribute to the same R package (weight measures frequency).

Table: **Structural Features of the Contributor Networks**

	Nodes	Edges	Avg. Weighted Degree	Diameter	Avg. Clustering Coefficient	Avg. Path Length	Connected Components
R	12,340	90,030	15.4	19	0.84	4.4	1,651
Python	43,376	1,079,426	72.8	11	0.87	3.39	1,833



Centrality Measures and Correlations

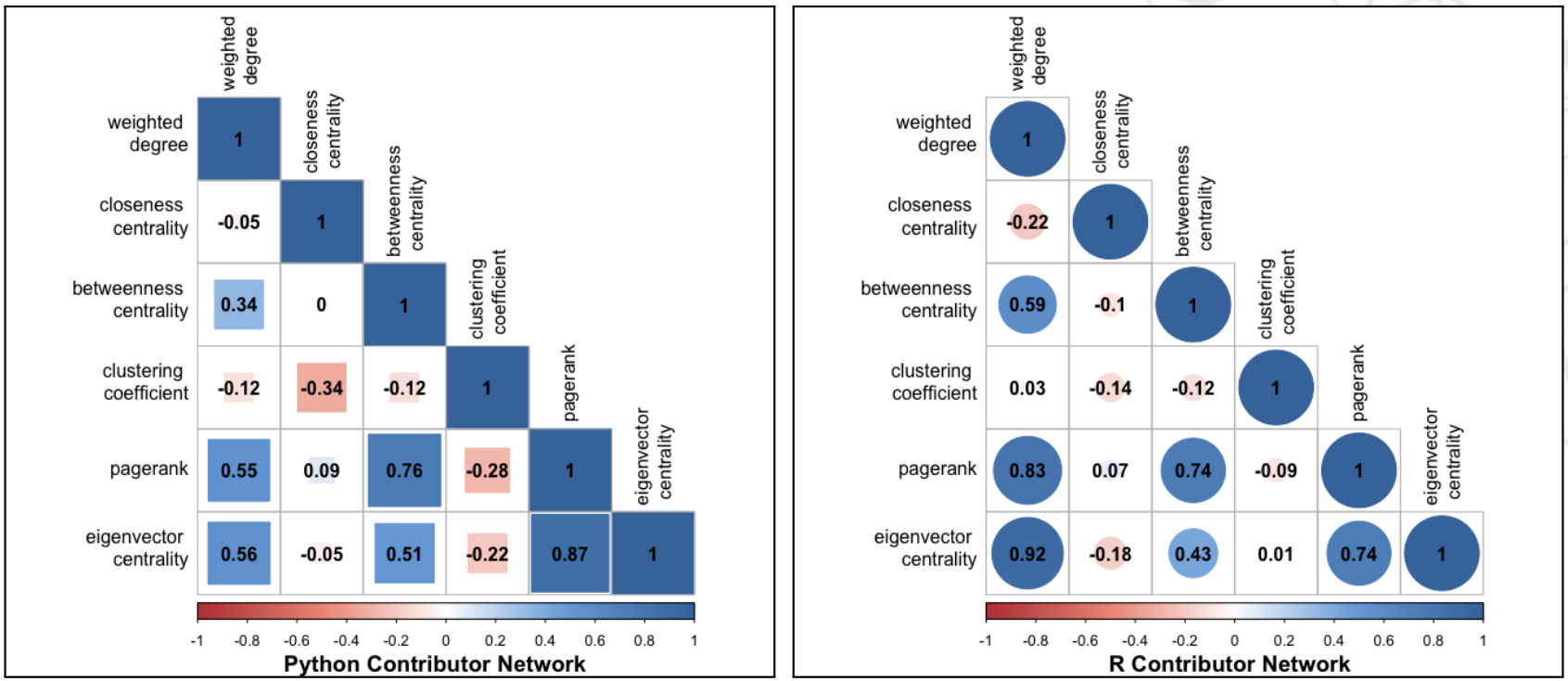


Figure: Pearson correlation coefficients between the centrality measures of the Python and R contributor networks

Modeling Framework

- Two Quasi-Poisson models using downloads and citations as dependent the variables, y. We let $E(y) = \mu$ and $Var(y) = \theta\mu$. We assume that $y_i \sim Poisson(\mu_i, \theta)$ and let the mean μ_i for the i^{th} observation vary as a function of the p covariates as follows: $\mu_i = e^{\beta_0 + \beta_1 x_{1,i} + ... + \beta_p x_{p,i}}$.
- p covariates: number of authors, number of commits, tag indicator, number of stars are used as package features, and network measures[1]
- For each package, we calculate weighted average of the degrees and centralities of the authors based on their percent contributions to the package.
- Three models are developed for each language.

[1] Some network characteristics were removed because of their high correlations with the other measures included in the models

Results - Full Model

	Variables	R Estimate (sign.)	Python Estimate (sign.)
Package Feature	(Intercept)	9.97 (***)	9.32 (***)
	tag indicator	0.27 (***)	0.12 (***)
	number of stars	0.02 (.)	0.07 (***)
	number of commits	0.03 (*)	0.08 (***)
	number of authors	0.02 ( )	0.05 (**)
Dependency Network	indegree	-0.13 (**)	0.01( )
	outdegree	0.15 (***)	0.06(***)
	closeness centrality	0.39 (***)	0.35 (***)
	betweenness centrality	0.06 (***)	0.02 (**)
	eigencentrality	-0.06 ( )	-0.06 (.)
	pagerank	0.12 (***)	0.09 (***)
	clustering	-0.03 ( )	-0.20 (***)
Contributor Network	weighted degree	0.21 (***)	0.14 (***)
	closeness	-0.15 (***)	-0.11 (***)
	clustering	0.14 (***)	-0.16 (***)

Standardized coefficient estimates: (***) 0.001 (**) 0.01 (*) 0.05 (.) 0.1

Concluding Remarks

Summary of Findings:

- The more derivative a package is, the less likely it is to have a high impact
- Network centrality measures are significant
- Introducing network features improves model performance

Challenges:

- Citations of sofware packages
- Number of downloads is imperfect
- Data availability
- Representativeness

Next steps:

- Expand set of languages
- Incorporate cost of development

Thank you!

- Questions/Feedback?
- Contact:

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