Trends in Topics in Software Engineering

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Abstract—Researchers should be able to explore software engineering, however their whims guide them. But do our current structure of conferences and journals inhibits that free exploration? To check this, this paper explores the trends in software engineering research within 35,391 Software Engineering(SE) papers from 34 leading SE venues over the last 25 years. These trends are discovered via a combination of (a) text mining; (b) Latent Dirichlet Allocation, to find the topics; (c) search-based software engineering, to automatically tune LDA; (d) clustering conferences and journals according to how often they publish on each topic. Trends in these topics reveal what topics are becoming more/less popular over time. Overlaps and gaps between conferences and journals are identified, from which we can identify what journals/ conferences might be merged and what new venues might be created to cover gaps. These results can be used for strategic and tactical purposes. Organizers of SE venues could use them as a long-term planning aid for improving and rationalizing how they service our research community. Also, individual researchers could also use these results to make short-term publication plans. Note that our analysis is 100% automatic, thus making it readily repeatable and easily updatable.

Index Terms—Software Engineering, Bibliometrics, Topic Modeling, Text Mining



1 Introduction

Each year, SE researchers submit papers to conferences, and journals. Significant effort is expended by the researchers writing and reviewing those papers and then (in the case of conferences) travelling and presenting papers. What can we learn about all those papers? What are the factors that prevent effective dissemination of research papers results? If we study patterns of acceptance in our SE papers, can we improve how we do, and report, research in software engineering?

For answers to these questions, this paper applies text mining and clustering using LDA (Latent Dirichlet Allocation) to 35,391 SE papers from the last 25 years published in 34 top-ranked conferences and journals (listed in Table 1). These venues are then clustered by what topics they share. Using these results:

- Organizers of SE venues can make long-term plans for rationalizing how they service this research community.
- Individual researchers can plan for short-term publications.

Further, using the text mining tools of this paper:

- Journal and conference organizers could find more relevant reviewers for a particular paper much faster.
- Research program managers could find more relevant reviewers much faster for grant proposals.
- University administrators could identify tired or emerging research trends. This could be used to plan academic hirings.
- The administrators of funding bodies could determine which areas of research are over/under-represented and, hence, those that are worthy of less/more funding (respectively).

When discussing these results with colleagues, sometimes they raise two issues. Firstly, some argue that if researchers know what kinds of papers are accepted at what venues, then that runs the risk of turning research into a "game" where authors deliberately distort their findings in order to increase the odds of getting papers accepted. Secondly, some argue this kind of meta-analysis is wrongly-directed since researchers should be free to explore whatever issues they like, without interference from

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some burdensome supervision body telling them what they can, or cannot research.

While these are all valid points, they actually endorse the need for this kind of study, for two reasons. Firstly, if there is some "game" where certain kinds of papers have a higher probability of getting accepted at certain kinds of venues, then it is important that everyone in the SE community knows the rules of that "game". This is important since:

- If we do not like those rules, then we should change them.
- If only some SE researchers know those rules, then that would be a disadvantage to other SE researchers who are unaware of the publication patterns if they unwittingly submit papers to venue X, when there exists another venue Y which might be more accepting.

Secondly, regarding academic freedom, we accept and strongly endorse the principle that researchers should be able to explore software engineering, however their whims guide them. But if the structure of SE venues is inhibiting, then that structure should change. This is an important point since, as discussed later, there are some troubling patterns within the SE literature:

- There exists different sets of topics that tend to be rejected from SE conferences or journals; researchers exploring some topics are systematically excluded from certain venues.
- There exists clusters of SE conferences which lack journal support. For researchers from institutions that favor journals over conferences, this means that authors of those conference papers may have challenges in retaining their position.
- We show below that a recent trend where SE conference papers are receiving significantly larger citations per year than journal papers. For academics whose career progress gets reviewed (e.g. during the tenure process; or if ever those academics are applying for new jobs), it is important to know what kinds of venues adversely effect citation counts.

In summary, this paper makes the following contributions:

- 1) A fully automatic and repeatable process for discovering a topology between tens of thousands of technical papers.
- 2) An application of that method to the SE literature.
- 3) An open-source toolkit that other researchers can apply to other sets of documents: see https://goo.gl/Au1i53.

Index	Short	Name	Type	Start	h5	Group
1	MDLS	International Conference On Model Driven Engineering Languages And Systems	Conf	2005	25	A1
	SOSYM	Software and System Modeling	Jour	2002	28	A2
2	S/W	IEEE Software	Jour	1991	34	B1
3	RE	IEEE International Requirements Engineering Conference	Conf	1993	20	C1
	REJ	Requirements Engineering Journal	Jour	1996	22	C2
4	ESEM	International Symposium on Empirical Software Engineering and Measurement	Conf	2007	22	D1
	ESE	Empirical Software Engineering	Jour	1996	32	D2
5	SMR	Journal of Software: Evolution and Process	Jour	1991	19	E1
	SQJ	Software Quality Journal	Jour	1995	24	E2
	IST	Information and Software Technology	Jour	1992	44	E3
6	ISSE	Innovations in Systems and Software Engineering	Jour	2005	12	F1
	IJSEKE	International Journal of Software Engineering and Knowledge Engineering	Jour	1991	13	F2
	NOTES	ACM SIGSOFT Software Engineering Notes	Jour	1999	21	F3
7	SSBSE	International Symposium on Search Based Software Engineering	Conf	2011	15	G1
	JSS	The Journal of Systems and Software	Jour	1991	53	G2
	SPE	Software: Practice and Experience	Jour	1991	28	G3
8	MSR	Working Conference on Mining Software Repositories	Conf	2004	34	H1
	WCRE	Working Conference on Reverse Engineering	Conf	1995	22	H2
	ICPC	IEEE International Conference on Program Comprehension	Conf	1997	23	Н3
	ICSM	IEEE International Conference on Software Maintenance	Conf	1994	27	H4
	CSMR	European Conference on Software Maintenance and Re-engineering	Conf	1997	25	H5
9	ISSTA	International Symposium on Software Testing and Analysis	Conf	1989	31	I1
	ICST	IEEE International Conference on Software Testing, Verification and Validation	Conf	2008	16	I2
	STVR	Software Testing, Verification and Reliability	Jour	1992	19	I3
10	ICSE	International Conference on Software Engineering	Conf	1994	63	J1
	SANER	IEEE International Conference on Software Analysis, Evolution and Re-engineering	Conf	2014	25	J2
11	FSE	ACM SIGSOFT Symposium on the Foundations of Software Engineering	Conf	1993	41	K1
	ASE	IEEE/ACM International Conference on Automated Software Engineering	Conf	1994	31	K2
12	ASEJ	Automated Software Engineering Journal	Jour	1994	33	L1
	TSE	IEEE Transactions on Software Engineering	Jour	1991	52	L2
	TOSEM	Transactions on Software Engineering and Methodology	Jour	1992	28	L3
13	SCAM	International Working Conference on Source Code Analysis & Manipulation	Conf	2001	12	M1
	GPCE	Generative Programming and Component Engineering	Conf	2000	24	M2
	FASE	International Conference on Fundamental Approaches to Software Engineering	Conf	1998	23	M3

TABLE 1: Corpus of venues (conferences and journals) studied in this paper. For a rationale of why these venues were selected, see §2.2. Note two recent changes to the above names: ICSM is now called ICMSE; and WCRE and CSMR recently fused into SANER. In this figure, the "Group" column shows venues that publish "very similar" topics (where similarity is computed via a cluster analysis shown later in this paper). The venues are selected in a diverse range of their h5 scores between 2010 and 2015. h5 is the h-index for articles published in a period of 5 complete years obtained from Google Scholar. It is the largest number "h" such that "h" articles published in a time period have at least "h" citations each.

ID	Name	Top 7 terms
0	Program Analysis	program, analysis, dynamic, execution, code, java, static
1	Requirements	requirements, design, systems, architecture, analysis, process, development
2	Metrics	metrics, data, quality, effort, prediction, defect, analysis
3	Applications	applications, web, systems, component, services, distributed, user
4	Performance	performance, time, data, algorithm, systems, problem, network, distributed
5	OOPS	object-oriented, programming, realtime, systems, section, functional, java
6	Testing	test, testing, cases, fault, techniques, coverage, generation
7	Source Code	code, source, information, tool, program, developers, patterns
8	Architecture	architecture, component, systems, design, product, reuse, evolution
9	Modeling	model, language, specification, systems, techniques, object, uml
10	Developer	developer, project, bug, work, open, team, tools

TABLE 2: The top 7 terms in the 11 major SE topics as found by this research. Generated by the LDADE system described in §2.1. Topics are ordered top-to-bottom, most-to-least frequent. Similarly, terms within topics are ordered left-to-right most-to-least frequent. The topic name shown in the left-hand-side column is derived from the most frequent terms.

- 4) A large database that integrates all our results into one, easy-to-query SQL database: see https://goo.gl/zSgb4i.
- 5) The identification of the 11 major topics in software engineering; see Table 2.
- 6) The creation of a "reader" of best papers in software engineering that lists the two most-cited papers within each of these 11 topics. See Table 3 and Table 4.
- 7) A temporal analysis showing how those groupings have changed over recent years.
- 8) Between the SE publication venues, overlaps and gaps are identified, from which we can identify what journals/conferences might be merged or created to cover gaps.
- 9) A previously unreported dichotomy between software conferences and journals. As shown later in this paper(§4.4), SE conference publications tend to publish on different topics to SE journals and those conferences publications earn a significantly larger number of citations than journal articles.

The rest of this paper is structured as follows. §2.1 describes our stable topic modeling (LDADE) approach to find representative topics in SE. A description of the data used in this study from various sources and its consolidation is described in Section §2.2. §3 finds that the topics generated by LDADE are reasonable. Hence, Secion §4 goes on to discuss the important patterns in those results. The threats to the validity of this study is described in Section §5.Section §6 gives an overview of prior and contemporary studies based on bibliometrics and topic modeling in SE literature. Recommendations based on this research are offered in Section §7 and finally, Section §8 concludes this study by presenting the inferences of this study and how it can aid the different sects of SE research community.

For the purposes of exposition, we will present our conclusions and recommendations in a forthright manner. But clearly, it is inappropriate for us to "demand" that the international SE research do anything at all. A more reasonable outcome of this paper would be to demonstrate the value of applying text mining tools to the products of SE research in order to better manage SE conferences and venues. Ideally, the professional societies that oversee SE conferences and journals should treat this entire paper

as a prototype of a report that they can run every year. Such a report would enable a data-driven approach to conference and journal management.

Note that a short two-page paper was previously published in the ICSE-17 companion [1]. Due to its small size, that document discussed very little of the details discussed here.

2 METHODS

2.1 Algorithms

One reason to prefer the analysis of this paper to prior results is our innovative use of the *stable* LDA algorithm called LDADE [2]. LDADE automatically tunes LDA's parameters (using DE) in order to remove unstable topics. Without LDADE, the results from using LDA can be subjective if a knowledge engineer uses "engineering insights" to set LDA's control parameters. However, with LDADE, those parameters are set using an optimization algorithm so LDADE is a fully automatic process.

Before describing LDADE, we first describe LDA.

2.1.1 LDA = Latent Dirichlet Allocation

As shown in Figure 1, LDA [3], [4] assumes D documents contain T topics expressed with W different words. Each document $d \in D$ of length N_d is modeled as a discrete distribution $\theta(d)$ over the set of topics. Each topic corresponds to a multinomial distribution over the words. Discrete priors α are assigned to the distribution of topics vectors θ and β for the distributions of words in topics.

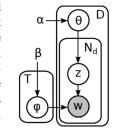


Fig. 1: LDA

As shown in Figure 1, the outer plate spans documents and the inner plate spans word instances in each document (so the *w*

node denotes the observed word at the instance and the z node denotes its topic). The inference problem in LDA is to find hidden topic variables z, a vector spanning all instances of all words in the dataset. LDA is a problem of Bayesian inference. The original method used is a variational Bayes approximation of the posterior

Topic	Top Papers							
Program Analysis	1992: Using program slicing in software maintenance; KB Gallagher, JR Lyle 2001: Dynamically discovering likely program invariants to support program evolution; MD Ernst, J Cockrell, WG Griswold, D Notkin							
Requirements	1992: A Software Risk Management Principles and Practices; BW Boehm 1995: A formal basis for architectural connection; R Allen, D Garlan							
Metrics	1996: A validation of object-oriented design metrics as quality indicators; VR Basili, LC Briand, WL Melo 1993: Object-oriented metrics that predict maintainability; W Li, S Henry							
Applications	2004: Qos-aware middleware for web services composition; L Zeng, B Benatallah, AHH Ngu, M Dumas, J Kalagnanam, H Chang 2011: CloudSim: a toolkit for modeling & simulation of cloud computing; R.Calheiros, R.Ranjan, A.Beloglazov, C.De Rose, R.Buyya							
Performance	1992: Spawn: a distributed computational economy; CA Waldspurger, T Hogg, BA Huberman 2003: Fault Localization With Nearest Neighbor Queries; M Renieris, SP Reiss							
OOPS	1996: The empirical investigation of Perspective Based Reading; VR Basili, S Green, O Laitenberger, F Lanubile, F Shull, LS Sorumgard 2006: Matters of Meta-Modeling; M Kuhne							
Testing	2004: Search-based software test data generation: A survey; P McMinn 2001: Prioritizing test cases for regression testing; G Rothermel, RH Untch, C Chu, MJ Harrold							
Source Code	2002: Two case studies of open source software development: Apache and Mozilla; A Mockus, RT Fielding, JD Herbsleb 2002: CCFinder: a multilinguistic token-based code clone detection system for large scale source code; T Kamiya, S Kusumoto, K Inoue							
Architecture	2000: A Classification and Comparison Framework for Software Architecture Description Languages; N Medvidovic, RN Taylor 2005: Software Reuse Research Status and Future; WB Frakes, K Kang							
Modelling	1997: The model checker SPIN; GJ Holzmann 1996: The STATEMATE semantics of statecharts; D Harel, A Naamad							
Developer	2009: Guidelines for conducting and reporting case study research in software engineering; P Runeson, M Host 2002: Two case studies of open source software development Apache and Mozilla; A Mockus, RT Fielding, JD Herbsleb							

TABLE 3: 25 years of SE papers. Most cited papers within our 11 SE topics. For a definition of these topics, see Table 2.

Topic	Top Papers						
Program Analysis	2012: Genprog: A generic method for automatic software repair; C Le Goues, TV Nguyen, S Forrest, W Weimer 2009: Automatically finding patches using genetic programming; W Weimer, TV Nguyen, C Le Goues, S Forrest						
Requirements	2009: A systematic survey of program comprehension through dynamic analysis; B Cornelissen, A Zaidman, A Van Deursen, R. Koschke 2009: Software architecture reconstruction: A process-oriented taxonomy; S Ducasse, D Pollet						
Metrics	2012: A systematic literature review on fault prediction performance in software engineering; T Hall, S Beecham, D Bowes, D Gray, S Counsell						
	2009: Predicting faults using the complexity of code changes; AE Hassan						
Applications	2011: CloudSim: a toolkit for modeling & simulation of cloud computing; R.Calheiros, R.Ranjan, A.Beloglazov, C.De Rose, R.Buyya 2011: A survey on privacy in mobile participatory sensing applications; D Christin, A Reinhardt, SS Kanhere, M Hollick						
Performance	2010: A theoretical and empirical study of search-based testing: Local, global, and hybrid search; M Harman, P McMinn						
	2011: Software module clustering as a multi-objective search problem; K Praditwong, M Harman, X Yao						
OOPS	2009: Incremental Clone Detection; N Gode, R Koschke						
	2014: Variability in Software Systems - A Systematic Literature Review; M Galster, D Weyns, D Tofan, B Michalik, Paris Avgeriou						
Testing	2011: An analysis and survey of the development of mutation testing; Y Jia, M Harman						
	2012: Regression testing minimization, selection and prioritization: a survey; S Yoo, M Harman						
Source Code	2010: DECOR: A method for the specification and detection of code and design smells; N Moha, YG Gueheneuc, L Duchien, AF Le Meur						
	2013: Feature location in source code: a taxonomy and survey; B Dit, M Revelle, M Gethers, D Poshyvanyk						
Architecture	2009: Software architecture many faces many places yet a central discipline; RN Taylor						
	2011: Reverse engineering feature models; S She, R Lotufo, T Berger, A Wasowski, K Czarnecki						
Modelling	2009: The "physics" of notations: toward a scientific basis for constructing visual notations in software engineering; D Moody						
	2009: The Palladio component model for model-driven performance prediction; S Becker, H Koziolek, R Reussner						
Developer	2009: Guidelines for conducting and reporting case study research in software engineering; P Runeson, M Host						
	2012: A decade of agile methodologies - Towards explaining agile software development; T Dingsoyr, SP Nerur, V Balijepally, NB Moe						

TABLE 4: Recent papers. Most cited papers, 2009-2016, within our 11 SE topics. For a definition of these topics, see Table 2.

distribution [3] and alternative inference techniques use Gibbs sampling [5] and expectation propagation [6].

There are many examples of the use of LDA in SE. For example, Rocco et al. [7] used text mining and Latent Dirichlet Allocation (LDA) for traceability link recovery. Guzman and Maleej perform sentiment analysis on App Store reviews to identify finegrained app features [8]. The features are identified using LDA and augmented with sentiment analysis. Thomas et. al. use topic modeling in prioritizing static test cases [9]. While all this work achieved useful results in their home domains, we prefer LDADE since it can automate the parameter tuning.

2.1.2 LDADE = LDA + Differential Evolution

Topic modeling is powered by three parameters; 1) k: Number of topics 2) α : Dirichlet prior on the per-document topic distributions 3) β : Dirichlet prior on the per-topic word distribution.

Research suggests that altering these parameters can result in unstable topics [7], [10]. Specifically, if the order of the input data is changed then the learned topics will also change. For example, in other work [2], we learned a table of 40 topics, each containing 10 words, from some Stackoverflow.com questions. That analysis was run twice, each time shuffling the input order of the data. Very large differences were seen in the table of learned topics: in only three cases were the exact same topics found in both runs while over half the time, most of the words in the topics were different.

To overcome the instability problem, these parameters need to be tuned to their optimal values. The simplest way of tuning them would be to explore the search space of these parameters exhaustively. This approach is called grid-search and was used in tuning topic modeling [11]. The prime drawback of this approach is the time complexity and can be very slow for tuning real numbers. Alternatively, numerous researchers recommend tuning these parameters using Genetic Algorithms(GA) [12], [13], [14]. In a GA, a population of candidate solutions are mutated and recombined towards better solutions. GA is also slow when the candidate space is very large and this is true for LDA since the candidates (α and β) are real valued. Manual tuning methods were successfully considered by some researchers [15], [16]. Due to

pragmatic reasons, these works failed to explore a large search space. In similar studies [17], the authors suggest using 67 topics (obtained by minimizing the log-likelihood error) and default values of α and β as provided by the LDA package in R statistical toolkit [18].

Recently [2] we used Differential Evolution (DE) to stabilize the LDA model which is much simpler to implement and also considers the effects of input data order. Inspired from the work by Fu et. al. on tuning learners in SE [19], this LDADE tool automatically tunes LDAs parameters in order to stabilize LDA model. They explored much larger range of tunings within tens of evaluations of the model, not hundreds or thousands.

Differential evolution just randomly picks three different vectors B, C, D from a list called F (the *frontier*) for each parent vector A in F [20]. Each pick generates a new vector E (which replaces A if it scores better). E is generated as follows:

$$\forall i \in A, E_i = \begin{cases} B_i + f * (C_i - D_i) & if \ \mathcal{R} < cr \\ A_i & otherwise \end{cases}$$
 (1)

where $0 \leq \mathcal{R} \leq 1$ is a random number, and f, cr are constants that represent mutation factor and crossover factor respectively(following Storn et al. [20], we use cr = 0.3 and f = 0.7). Also, one value from A_i (picked at random) is moved to E_i to ensure that E has at least one unchanged part of an existing vector. The objective of DE is to maximize the Raw Score (\Re_n) which is similar to the Jaccard Similarity [15]. Agrawal et. al. [2] have explained the \Re_n in much more detail.

After tuning on the data described in the next section, we found that optimal values in this domain are k, α & β are 11, 0.847 & 0.764 respectively.

2.1.3 Topical Clustering

After categorizing the papers in SE into a set of topics, the venues are clustered with respect to these topics. The clustering technique adopted is the linkage based hierarchical clustering algorithm using the *complete* scheme [21]; i.e. Topics are hierarchically clustered using the terms associated with them.

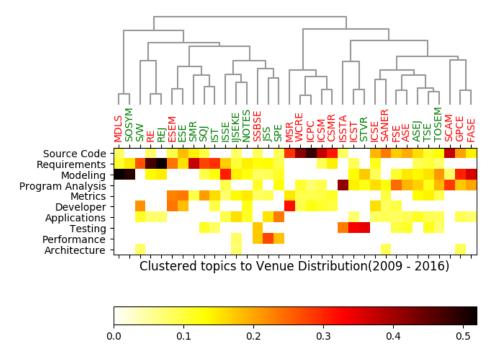


Fig. 2: Hierarchical clustering heatmap of Topics and Venues between the years 2009-2016. Along the top, green denotes journals and red denotes a conference. Along the left side, the black words are the topics of Table 2. Topics are sorted top-to-bottom, most-to-least frequent. Each cell in the heatmap depicts the frequency of a topic in a particular venue. The tree diagrams above the venues show the results of a bottom up clustering of the venues with respect to the topics. In those clusters, venues are in similar sub-trees if they have similar pattern of topic frequencies.

For example, Figure 2 shows the results of this hierarchical clustering technique on papers published between 2009 and 2016. Topics are represented on the vertical axis and venues are represented on the horizontal axis. The **green** venues represents journals and the **red** represents conferences. Each cell in the heatmap indicates the contribution of a topic in a venue. Darker colored cells indicate strong contribution of the topic towards the venue while a lighter color signifies a weaker contribution. The clusters are represented using dendograms and can be seen along the horizontal axis of Figure 2. Lower the height of the dendogram, stronger the cohesion of the clusters.

2.2 Data

Using LDADE and topical clustering, we have analyzed the trends and construct the topics in SE literature, we build a repository of 35,391 papers and 35,406 authors from 34 SE venues over a period of 25 years between 1992-2016. This time period (25 years) was chosen since it encompasses recent trends in software engineering such as the switch from waterfall to agile; platform migration from desktops to mobile; and the rise of cloud computing. Another reason to select this 25 year cut off was that we encountered increasingly more difficulty in accessing data prior to 1992; i.e. before the widespread use of the world-wide-web.

As to the venues used in this study, these were selected via a combination of on-line citation indexes (Google Scholar), feedback from the international research community (see below) and our own domain expertise:

 Initially, we selected all the non-programming language peerreviewed conferences from the "top publication venues" list of Google Scholar Metrics (Engineering and Computer Science,

- Software Systems). Note that Google Scholar generates this list based on citation counts.
- Initial feedback from conference reviewers (on a rejected earlier version of this paper) made us look also at SE journals.
- To that list, using our domain knowledge, we added venues that we knew were associated with senior researchers in the field; e.g. the ESEM and SSBSE conferences.
- Subsequent feedback from an ICSE'17 companion presentation [1] about this work made us add in journals and conferences related to modeling.

This resulted in the venue list of Table 1.

For studying and analyzing those venues we construct a database of 18 conferences, 16 journals, the papers published with the metadata, authors co-authoring the papers and the citation counts from 1992-2016. Topics for SE are generated using the titles and abstracts of the papers published in these venues rather than the entire text of the paper. Titles and abstracts have been widely used in text based bibliometric studies [17], [22], [23] primarily due to three reasons: (a) Titles and abstracts are designed to index and summarize papers; (b) Obtaining papers is a huge challenge due to copyright violations and its limited open source access; (c) Papers contain too much text which makes it harder to summarize the content. Abstracts on the other hand are much more succinct and generate better topics.

The data was collected in four stages:

 Venues are first selected manually based on top h5-index scores from Google Scholar. It should be noted that all the data collection method is automated if the source of papers from a desired venue is provided. Thus, this can be expanded to additional venues in the future.

- 2) For each venue, DOI (Document Object Identifier), authors, title, venue & year for every publication between 1992-2016 is obtained by scrapping the html page of DBLP¹. DBLP (DataBase systems & Logic Programming) computer science bibliography is an on-line reference for bibliographic information on major computer science publications. As of Jan 2017, dblp indexes over 3.4 million publications, published by more than 1.8 million authors.
- 3) For each publication, the abstract is obtained from the ACM portal via AMiner² [24] periodically on their website. Abstracts for 21,361 papers from DBLP can be obtained from the ACM dump. For rest of the papers, we use only the tiles for the subsequent study.
- 4) For each publication, we obtain the corresponding citation counts using crossref's REST API.

Since the data is acquired from three different sources, a great challenge lies in merging the documents. There are two sets of merges in this data:

- Abstracts to Papers: A merge between a record in the ACM dump and a record in the DBLP dump is performed by comparing the title, authors, venue and the published year. If these four entries match, we update the abstract of the paper in the DBLP dump from the ACM dump. To verify this merge, we inspected 100 random records manually and found all these merges were accurate.
- Citation Counts: DOIs for each article can be obtained from the DBLP dump, then used to query crossref's rest API to obtain an approximate of the citation count. Of the 35,391 articles, citation counts were retrieved for 34,015 of them.

3 SANITY CHECKS

Before delving into the results of the research it is necessary to critically evaluate the topics generated by LDADE and the clustering of venues.

3.1 Are our Topics "Correct"?

Several aspects of Figure 2 suggest that our topics are "sane". Firstly, in that figure, we can see several examples of specialist conferences paired with the appropriate journal:

- The main modeling conference and journal (MDLS and SOSYM) are grouped together;
- The requirements engineering conference and journal are grouped together: see RE+REJ;
- The empirical software engineering conference and journals are also grouped: see ESEM+ESE;
- Testing and verification venues are paired; see ICST+STVR.

Secondly, the topics learned by LDADE occur at the right frequencies in the right venues:

- The modeling topics appears most frequently in the modeling conference and journal (MDLAS and SOSYM);
- The requirements topic appears most frequently in RE and REJ; i.e. the requirements engineering conference and journal.
- The testing topic appears most frequently in the venues devoted to testing: ISSTA, ICST, STVR;
- 1. http://dblp.uni-trier.de/
- 2. https://aminer.org/citation
- 3. https://www.crossref.org/

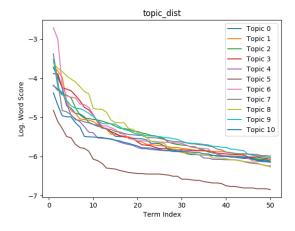


Fig. 3: Log Score of terms in each topic.

- The metrics topic occurs most often at venues that discuss ways to empirically assess software engineering methods: ESEM and ESE.
- The source code topic occurs most often at venues that focus most on automatic code analysis: ICSM, CSMER, MSR, WCRE, ICPC.

3.2 Are 11 Topics Enough?

After instrumenting the internals of LDADE, we can report that the 11 topics Table 2 covers 90% of the papers. While our LDADE reported many more topics than these top 11, those occur at diminishingly low frequencies. As evidence of this, recall that the rows of Figure 2 are sorted top-to-bottom most-to-least frequent. Note that the bottom few rows are mostly white (i.e. occur at very low frequency) while the upper rows are much darker (i.e. occur at much higher frequency). That is, if we reported *more* than 11 topics then the 12th, 13th etc would occur at very low frequencies.

We note that this study is not the only one to conclude that SE can be reduced to 11 topics Other researchers [23], [25], [26] also report that 90% of the topics can be approximated by about a dozen topics.

3.3 Are Our Topics Correctly Labelled?

Another question to ask is whether or not the topics of Table 2 have the correct labels. For example, we have assigned the label "Program analyis" to the list of terms "program, analysis, dynamic, execution, code, java, static". More generally, we have labelled all our topics using first one or two words. Is that valid?

Figure 3 shows the LDA score for each term in our topics. The x-axis orders the terms in same order as the right-hand-column of Table 2. The y-axis of that plot logarithmic; i.e. there is very little information associated with the latter words. Hence, the evidence to hand suggests that generated labels from the first few terms is valid.

4 RESULTS

Given that our approach has passed the sanity checks of the last section, we can now use these results to gain insight into the nature of contemporary software engineering research. More specifically, we can ask the following research questions:

- **RQ1:** What SE venues are missing?
- **RQ2:** What SE venues might be merged?
- **RQ3:** What SE topics are growing or shrinking?
- RQ4: Do SE conferences & journals accept different topics?

4.1 RQ1: What SE venues are missing?

Using these results, we can infer what venues should be created. Most of the venue clusters of Figure 2 show sets of conferences serviced by a related journal; e.g.

- MDLS and SOSYM, for modeling;
- RE and REJ, for requirements;
- EMSE and ESE, for metrics.
- ISSTA, ICST and STVR, for testing;

The glaring exception to these are the conferences that contain many papers relating to the source code topic:

• ICSM, CSRM, MSR, WCRE, ICPC;

As shown in Figure 2, many papers at these conferences explore the Source Code topic. Yet the only journal that takes papers on source code is ESE (the empirical software engineering journal)—and as shown in Figure 2, that topic is only a weak focus of that journal. Hence we would recommend either:

- Adjusting the associate editors of some journals in order to encourage and accept more source code papers;
- Creating a new journal to handle the numerous conferences that especially focus on source code.

4.2 RQ2: What SE venues might be merged?

Another way to use Figure 2 might be to merge venues that process similar topics. For example:

- It is not clear that our community needs three generalist SE journals such as TOSEM, TSE, and ASEJ. As shown in Figure 2, these journals publish similar kinds of papers.
- Also, SQJ and IST are two journals that process papers with very similar topics.
- Further, JSS and SPE are another pair of journals that process very similar papers (exception: JSS focuses more on performance while SPE focuses more on applications).
- Lastly, the cluster of CSM, CSRM, MSR, WCRE, ICPC explore such similar topics that it might be useful to merge some

of these meetings. Interesting, recalling the above historical note, our community is already taking steps on the second point (merging WCRE and CSMR into SANER).

4.2.1 Why Merge Conferences?

We suggest merging SE conferences since the SE conference calendar is overcrowded and that crowding is detrimental to:

- The creation of new communities exploring newer ideas;
- The collaboration between existing communities.

For example:

- In 2016, the ASE, ESEM and RE conferences all ran at the same time. Also, in 2017, FSE'17 and RE'17 will run concurrently. This means that these communities will be unable to collaborate with each other.
- The FSE'17 workshop submission date was 2 weeks after the FSE rebuttal week and one week after the ASE submission date. SE researchers were so exhausted after all that work that the FSE workshops received very few submissions.

This last example, about the FSE workshops is particularly troubling since workshops are where new communities meet to experiment with new ideas. When our conference timetable is so tight that those new communities have no place to grow, then we need to change that timetable. To solve this problem, we propose two strategies:

- For venues with much overlap, these could be run on alternating years.
- Alternatively, we could encourage more churn in the list of active SE conferences. After (say) 5 years of operation, then all venues get assessed for overlap with existing venues. Older venues with much overlap should be merged, thus making space for newer conferences with newer ideas.

4.2.2 But Why Merge Journals?

One of us (Menzies in Figure 4) serves as associate editor on several of the journals which are candidates for merging. Based on that experience, we note there are several advantages in merging journal.

Firstly, the more venues, the more reviewers must pick and choose what reviews to accept or complete in a timely manner. For example, Menzies' experience is that reviewers are often

	Reviewer Name	Board Member	Classifications	Reviewer Statistics (Agreed Invitations)		Invitation Statistics	
	Tim Menzies (Reviewer)	No		Reviews in Progress:	0	Date Last Invited:	04 Dec 2016
	North Carolina State Univer	sity		Completed Reviews:	58	Outstanding Invitations:	0
				Un-assigned After Agreeing	j: 2	Agreed:	62
ESE:				Terminated After Agreeing:	2	Declined:	2
ESE:				Last Review Agreed:	04 Dec 2016	Un-invited Before Agreeing:	1
				Last Review Completed:	04 Dec 2016	Terminated:	2
				Last Review Declined:	04 Dec 2015	Total Invitations:	67
				Avg Days Outstanding:	26		
				Manuscript Rating:	0		
				Avg Review Rating:	87.5		
	Reviewer Name	Board Member Cla		eviewer Statistics Agreed Invitations)	:	Invitation Statistics	
	Tim Menzies (Reviewer)	No	Re	eviews in Progress:	0	Date Last Invited:	12 Dec 2015
			Co	ompleted Reviews:	16	Outstanding Invitations:	0
			Ur	n-assigned After Agreeing:	0	Agreed:	17
A CEL			Te	erminated After Agreeing:	1	Declined:	1
ASEJ:			La	st Review Agreed:	12 Dec 2015	Un-invited Before Agreeing:	0
			La	st Review Completed:	12 Dec 2015	Terminated:	0
			La	st Review Declined:	24 Apr 2012	Total Invitations:	18
			Av	vg Days Outstanding:	37		
			Ma	anuscript Rating:	0		
			Av	vg Review Rating:	0.0		

Fig. 4: Meta-knowledge about a reviewer.

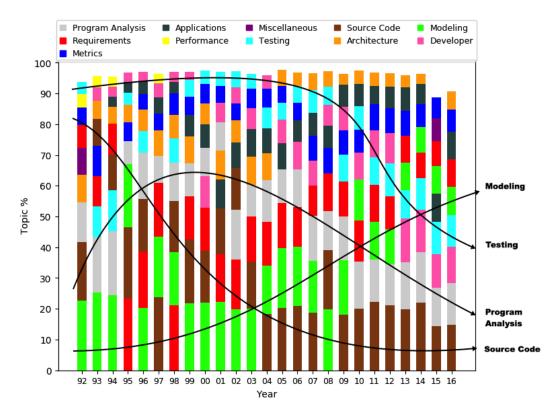


Fig. 5: Changes in **conference** topics, 1992-2016. Arrows are used to highlight the major trends. This is a *stacked* diagram where, for each year, the *most* popular topic appears at the *bottom* of each stack. That is, as topics become *more* frequent, they fall towards the *bottom* of the plot. Conversely, as topics become *less* frequent, then rise towards the *top*.

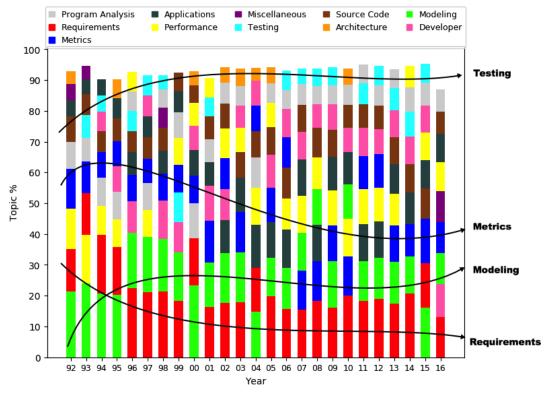


Fig. 6: Changes in **journal** topics, 1992-2016. Same format as Figure 5. Note that some popular conference topics (e.g. source code, program analysis, testing) are currently *not* popular journal topics.

unresponsive to review requests from lesser-ranked journals. This is one reason to endorse the proposal listed above to merge (SQJ+IST) and (JSS+SPE) since, for both pairs, one journal is much higher-ranked than the other (see https://goo.gl/ti7vd4).

Secondly, the more venues, the less likely that meta-knowledge about a reviewer is collected and available for use by associate editors. Such meta-information is useful for pre-checking that reviewers might complete their tasks in a timely manner. For example Figure 4 shows meta-knowledge for one reviewer from the ESE and ASEJ editorial managers. While this reviewer is the same person, ESE editors would have a different opinion of this reviewer than ASEJ:

- ESE says this reviewer has an average review rating of 87% but ASEJ editors cannot access those ratings.
- ESE thinks this reviewer averages 26 days to complete reviews but the ASEJ review system knows that this reviewer can be slower than that (37 days before return a review).
- The sum of "uninvited" and "terminated" fields in ESE is much higher in ESE than ASEJ. So ASEJ might think this reviewer is very reliable but the ESE editors might have some doubts.

Ideally, all SE venues (conferences and journals) have access to consistent meta-knowledge about who is a good and bad reviewer. Unfortunately, given our proliferation of venues, such meta-knowledge is not maintained consistently within our community.

The counter argument to this section is that journals should not be merged since this could force very different research communities into an awkward combination. Hence, we take care only to suggest mergers between journal venues with very similar topic profiles, as shown by Figure 2.

4.3 RQ3: What SE topics are Growing or Shrinking?

Figure 5 and Figure 6 show how the topics change in conferences and journals over the last 25 years of software engineering. These are *stacked diagrams* where, for each year, the *more popular* topic appears *nearer the bottom* of each stack. Arrows are added to highlight major trends in our corpus:

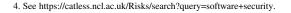
- Downward arrows denote topics of increasing popularity.;
- *Upward* arrows show topics of *decreasing* popularity.

One clear trend in both figures is that some topics are far more popular than others. For example, at the conferences(Figure 5):

- Source code, program analysis, and testing have become very popular topics in the last decade.
- Performance and security concerns have all disappeared in our sampled venues. Performance appears, a little, in journals but is far less popular that many other topics.
- Modeling is a topic occurring with decreasing frequency in our sample.

This is *not* to say that performance, modeling and security research has "failed" or that no one works on this topics anymore. Rather, it means that those communities have moved out of mainstream SE to establish their own niche communities.

As to the low occurrence of performance and the absence of any security terms in Table 2, this is one aspect of these results that concerns us. While we hear much talk about security at the venues listed in Table 1, Figure 5 and Figure 6, security research is not a popular topic in mainstream software engineering. Given the current international dependence on software, and all the security violations reported due to software errors⁴, it is surprising and



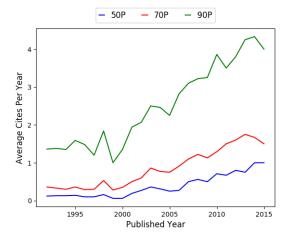


Fig. 7: Median(**50P**), 70^{th} Percentile(**70P**) and 90^{th} Percentile(**90P**) of average cites per year for articles published in SE venues between 1992-2015.

somewhat alarming that security is not more prominent in our community. This is a clear area where we would recommend rapid action; e.g.

- Funding bodies should consider increasing the funding allocated to software security projects;
- Editors of software journals might consider: increasing the number of special issues devoted to software security;
- Organizers of SE conferences might consider changing the focus of their upcoming events.

4.4 RQ4: Do Conferences and Journals Accept Different Topics?

Figure 5 and Figure 6 report stark differences between the kinds of topics published at SE journals and conferences. For example:

- In journals, metrics, modeling and requirements appear quite
 often. But in conferences they appear either rarely or (in the
 case of modeling) remarkably decreasing frequency in the last
 decade.
- In conferences, source code, program analysis, and testing appear have become very prominent in the last decade but these topics barely appear in journals.

Hence, we say that SE journals and SE conferences clearly accept different kinds of papers. Is this a problem? Perhaps so. Using our data, we can compute the number of citations per year for papers published at different venues. For example, Figure 7 shows that the 50th, 70th, 90th percentiles of cites per year has been steadily increasing since 2000. Table 5 shows the same data but this time broken out into conferences and journals:

- A red background indicates when conferences are receiving more citations per year;
- A green background indicates when journals papers are receiving more citations per year;
- Otherwise, there is no statistically difference between the two distributions.

For this analysis, "more citations" means that the distributions are statistically significantly different (as judged via the 95% confident bootstrap procedure recommended by Efron & Tibshirani [27, p220-223]) and that difference is not trivially small (as judged by the A12 test endorsed by Arcuri et al. at ICSE '11 [28]).

Year	Conference				Journal				
Year	50P	70P	90P	IQR	50P	70P	90P	IQR	
1992	0.08	0.12	0.2	0.2	0.12	0.4	1.56	0.6	
1993	0.08	0.29	0.71	0.33	0.13	0.33	1.58	0.46	
1994	0.09	0.26	0.78	0.35	0.13	0.35	1.7	0.43	
1995	0.27	0.5	1.14	0.64	0.14	0.36	1.59	0.45	
1996	0.1	0.24	0.9	0.33	0.05	0.29	1.76	0.48	
1997	0.1	0.25	0.9	0.3	0.1	0.4	1.55	0.5	
1998	0.26	0.58	1.32	0.63	0.11	0.42	1.89	0.63	
1999	0.06	0.17	0.72	0.28	0.06	0.33	1.11	0.5	
2000	0.12	0.41	1.29	0.59	0.06	0.29	1.35	0.47	
2001	0.13	0.38	1.06	0.5	0.25	0.75	2.63	1.0	
2002	0.2	0.53	1.4	0.6	0.27	0.8	2.73	1.13	
2003	0.29	0.64	1.86	0.71	0.36	1.0	2.71	1.14	
2004	0.23	0.54	2.0	0.69	0.38	1.0	2.69	1.23	
2005	0.33	0.67	1.83	0.75	0.25	0.75	2.67	0.92	
2006	0.18	0.64	1.91	0.82	0.45	1.09	3.55	1.36	
2007	0.4	0.9	2.6	1.0	0.5	1.3	3.9	1.5	
2008	0.44	1.0	2.67	1.11	0.78	1.56	4.0	1.78	
2009	0.38	1.0	2.63	1.0	0.63	1.5	3.63	1.75	
2010	0.57	1.29	3.29	1.43	0.71	1.43	4.14	1.71	
2011	0.67	1.33	3.17	1.5	0.67	1.67	4.0	1.83	
2012	0.8	2.3	4.4	2.0	0.8	1.4	3.2	1.6	
2013	0.75	2.25	5.25	2.5	0.75	1.75	4.0	1.75	
2014	1.0	2.0	5.0	2.0	0.67	1.67	4.0	2.0	
2015	1.0	2.0	4.0	2.0	0.5	1.5	3.5	2.0	

TABLE 5: Median(50P), 70^{th} Percentile(70P), 90^{th} Percentile(90P) and Inter Quartile Range(IQR) of average cites per year for articles published in conferences and journals between 1992-2015 (IQR=inter-quartile range= (75-25)th range). Column one colors denote the years when either Conferences or Journals received a statistically significantly larger number of citations per year.

Journal

Conference

Note that until very recently (2009), journal papers always achieved statistically more cites per year than conference papers. However, that trend is over. Since 2012, conference papers now receive more cites per year. This statistic can justify Fernandes' 2014 study [29] where he states that since 2008, there has been a significant increase(almost double) in the number of conference publications over journal articles. For journal editors, this is a troubling trend. Consider a junior faculty member who now knows that conference papers receive statistically larger cites per year than journals. This could result in one of the "gaming" tactics discussed in our introduction; i.e. those new faculty might elect to:

- Work less on metrics, modeling and requirements since these are not popular journal topics;
- And work more on testing, program analysis and source code, since these appear more often in conferences where they could receive more citations per year.

There any many actions journal editors could undertake to mitigate this problem. For example, a recent trend in SE conferences are the presentation of "Journal-First" papers that have already appeared in journals. Since they are being seen by a larger audience, such journal-first papers might receive more citations per year. Also, once a journal becomes known for a Journal-first program, then that could increase the number of submissions to that journal.

5 THREATS TO VALIDITY

This paper is less prone to *tuning bias* and *order bias* that other software analytics papers. As discussed earlier in section 2.1, we use search-based SE methods to find our tunings and those tunings are selected to mitigate against the effects of changing the order of the training example

The main threat to validity of our results is *sampling bias*. This study can access the accepted papers *but not the rejected ones*. Perhaps if both accepted and rejected papers are studied, then some patterns other that the ones reported here might be discovered.

That said, sampling those rejected papers is problematic. We can access 100% of accepted papers via on-line means. Sampling rejected papers imply asking researchers to supply their rejected papers. The experience in the research community with such surveys is that only a small percent of respondents reply [30] in which case we would have a second sampling bias amongst the population of rejected papers. Additionally, most researchers alter their rejected papers in-line with an alternate conference/journal and make a new submission to the venue. At the time of this writing, we do not know how to resolve this issue.

6 RELATED WORK

To the best of our knowledge, this paper is the largest study of the SE literature yet accomplished (where "large" is measured in terms of number of papers and number of years).

Unlike prior work [26], [31], [32], [33] our analysis is fully automatic and repeatable. The same is not true of other studies. For example, the Ren and Taylor [32] method of ranking scholars and institutions incorporate manual weights assigned by the authors. Those weights were dependent on expert knowledge and has to be updated every year. Our automation means that this analysis is quickly repeatable whenever new papers are published.

Another difference between our study and the papers mentioned below is our use of the stable LDADE algorithm. As mentioned above, LDADE automatically tunes LDAs parameters (using DE) inorder to remove unstable topics.

6.1 Bibliometrics Based Studies

Multiple bibliometric based studies have explored patterns in SE venues over the last decades. Some authors have explored only conferences [34], [35] or journals [36] independently while some authors have explored both a mixture of both [23], [29], [32].

Early bibliometric studies were performed by Ren & Taylor in 2007 where they assess both academic and industrial research institutions, along with their scholars to identify the top ranking organizations and individuals [32]. They provide an automatic and versatile framework using electronic bibliographic data to support such rankings which produces comparable results as those from manual processes. This method although saves labor for evaluators and allow for more flexible policy choices, the method does not provide a spectrum of the topics and the publication trends in SE.

Later in 2008, Cai & Card [23] analyze 691 papers from 14 leading journals and conferences in SE. They observe that 89% of papers in SE focus on 20% of the subjects in SE, including software/program verification, testing and debugging, and design tools and techniques. We repeat this study over a wider spread of publications, venues and authors (see §2.2) and the results conform with their observations.

In 2012, Hamadicharef performed a scientometrics study on IEEE Transactions of Software Engineering (TSE) for three decades between 1980-2010 [36]. He analyzes five different questions

 Number of publications: A quasi-linear growth in number of publications each year.

- Authorship Trends: It is observed that, a large number of articles in the 80s had only one or two co-authors but since the turn of the century it seemed to increase more papers having 5, 6 or 7 co-authors.
- Citations: The most cited TSE paper in this period had 811 cites and on an average a paper was cited 22.22 times with a median of 9 cites. On the other hand 13.38% papers were never cited. A larger study over 34 venues was repeated in this paper comparing the citation trends between conferences and journals (See §4.4).
- Geographic Trends: 46 different countries contribute to TSE between this period. 57% of the contributions to TSE come from USA, close to 21% come from Europe and less than 1% publications come from China.
- # of References: The average number of references per article increases 12.9 to 42.9 between 1980 to 2010.

A much larger study using 70,000 articles in SE was conducted in 2014 by Fernandes [29]. He observes that the number of new articles in SE is double on an average every decade and since 2008 conferences publish almost twice as many papers as journals every year. Similar to Hamadicharef's work [36] it fails to address how the citation trends have been varying between conferences and journals and if it attributes towards the increased number of publications in conferences over journals.

More recently, Garousi and Fernandes [37] et. al. performed a study based on citations to identify the top cited paper in SE. This study was based on two metrics: a) total number of citations and b) average annual number of citations to identify the top papers. The authors also go to the extent of characterizing the overall citation landscape in Software Engineering hoping that this method will encourage further discussions in the SE community towards further analysis and formal characterization of the highlycited SE papers.

Geography based bibiliometric studies on Turkish [38] and Canadian [39] SE communities were performed by Garousi et. al. to study the citation landscape in the respective countries. They identify a lack of diversity in the general SE spectrum for example, limited focus on requirements engineering, software maintenance and evolution, and architecture. They also identify a low involvement from the industry in SE. Since these studies were localized to a certain country, it explored lesser number of papers

Citation based studies have also evolved into adoption of measures such as h-index and g-index to study the success of an SE researcher. Hummel et. al. in 2013 analyzes the expressiveness of modern citation analysis approaches like h-index and g-index in SE by analyzing the work of almost 700 researchers in SE [40]. They conclude that on an average h-index for a top author is around 60 and g-index is about 130. The authors use citations to rank authors and some researchers are apprehensive to this definition of success [29], [41].

Vasilescu et. al. study the health of SE conferences with respect to community stability, openness to new authors, inbreeding, representatives of the PC with respect to the authors community, availability of PC candidates and scientific prestige [35]. They analyze conference health using the R project for statistical computing to visualize and statistically analyze the data to detect patterns and trends [42]. They make numerous observations in this study

 Wide-scoped conferences receive more submissions, smaller PCs and higher review load compared to narrow scoped conferences.

- Conferences considered in the study are dynamic and have greater author turnover compared to its previous edition.
- Conferences like ASE, FASE and GPCE are very open to new authors while conferences like ICSE are becoming increasingly less open.
- Lesser the PC turnover, greater the proportion of papers accepted among PC papers.
- Narrow-scoped conferences have more representative PCs than wide-scoped ones.
- Not surprisingly, the higher the scientific impact of a conference, the more submissions it attracts and tend to have lower acceptance rates. The authors work is very detailed and gives a detailed summary of SE conferences.

Although this paper is very extensive, the authors do not explain the topics associated with venues ($\S 3.3$ and $\S 4.3$) or how conferences and journals are similar/different from each other($\S 4.4$).

6.2 Topic Modeling

Another class of related work are *Topic Modeling* based studies which has been used in various spheres of Software Engineering. According to a survey reported by Sun et. al. [43], topic modeling is applied in various SE tasks, including source code comprehension, feature location, software defects prediction, developer recommendation, traceability link recovery, re-factoring, software history comprehension, software testing and social software engineering. There are works in requirements engineering where it was necessary to analyze the text and come up with the important topics [44], [45], [46]. People have used topic modeling in prioritizing test cases, and identifying the importance of test cases [47], [48], [49]. Increasingly, it has also become very important to have automated tools to do SLR [50]. We found these papers [51], [52], [53] who have used clustering algorithms (topic modeling) to do SLR.

Outside of SE, in the general computer science (CS) literature, a 2013 paper by Hoonlor et. al. highlighted the prominent trends in CS [54]. This paper identified trends, bursty topics, and interesting inter-relationships between the American National Science Foundation (NSF) awards and CS publications, finding, for example, that if an uncommonly high frequency of a specific topic is observed in publications, the funding for this topic is usually increased. The authors adopted a Term Frequency Inverse Document Frequency (TFIDF) based approach to identify trends and topics. A similar approach can be performed in SE considering how closely CS is related to SE.

Garousi and Mantyla recently have adopted a Topic Modeling and Word Clustering based approach to identify topics and trends in SE [17] similar to the research by Hoonloor et. al. [54]. Although their method is very novel and in line with the current state of the art, they use only the titles of the papers for modeling topics. This might lead to inaccurate topics as titles are generally not very descriptive of the field the paper is trying to explore. This issue is addressed in the current work where we use the abstracts of the paper which gives more context while building models.

In 2016, Datta et. al. [25] used Latent Dirchlet Allocation to model 19000 papers from 15 SE publication venues over 35 years into 80 topics and study the half life of these topics. They coin the term "Relative Half Life" which is defined as the period between which the "importance" of the topic reduces to half. They further define two measures of importance based on the citation half life and publication half life. The choice of 80 topics is based on lowest

log likelihood and although very novel the authors do not shed light on the individual topic and the terms associated with it. Note that we do not recommend applying their kind of analysis since it lacks automatic methods for selecting the control parameters for LDA. Our automatic methods for finding those control parameters are described in $\S 2.1$.

7 RECOMMENDATIONS

Based on this paper, we offer the following set of recommendations as a demonstration of what can be done with this kind of data. For the purposes of exposition, we state these recommendations in a forthright manner. However, we do not presume that the SE community "must" do any of the following. That said, we do say that the following recommendations raise serious issues that need to be debated within our community.

7.1 Merge Some Conferences

There exists active research communities without strong journal-level support. For historical reasons, this paper, has identified that community as ICSM, CSRM, MSR, WCRE, ICPC (which might better be called ICSME, MSR, ICPC due to recent changes at those venues). Given the excessive over-crowding of the SE conference calendar, we strongly recommend always monitoring the current set of conferences and merging those that explore similar topics.

Further to this point, we would also propose a "five year rule" where new venues can exist and evolve for a period of time (e.g. five years) before their steering committees consider merging with other venues.

7.2 Merge Some Journals

There exists three generalists SE journals (TOSEM, TSE, ASEJ) that all explore the same wide range of topics. If these journals were merged, that would give editors more opportunity to accumulate important knowledge about what reviewers are better at reviewing than others.

Also, there exists two pairs of specialized SE journals that all explore the same topics: (JSS+SPE), (SQJ+IST). Within each pair, one journal is far more prestigious than the other. Given the problems associated with collecting reviews for the less-ranked journal, there could be advantages to merging these conferences.

7.3 Create, or Significantly Change, some Journals

Not only should some existing journals be merged, but it might be useful to create new ones. Researchers exploring testing, program analysis and source code are far less likely to achieve journal publication than those exploring methods, modeling, and requirements. We note that some new journal focusing on source code would address the recommendation proposed above. Other new journals that seem to be required are those focusing more on program analysis and testing.

Further to this point, one way to create a "new' journal would be to "retool" an existing one. This lack of extensive journal-level support for program analysis, and source code topics could be meet by existing journals that:

 Create special issues devoted to topics currently underrepresented at the journal level.

- Establish a journal-first program with conferences devoted to these topics: i.e. ICSME, MSR, ICPC (for source code); and ISSTA, FSE, SCAM (for program analysis).
- Significantly extended (or even replace) their current editorial board with specialists in testing, program analysis, and source code.

7.4 Watch the Citation Rates

This study found a new effect in software engineering: in the last five years, for the first time in the history of SE, conference papers started earning significantly large cites per year than journal papers. This effect merits our careful attention since, if it persists and extends, then this would imply a much larger reorganization of our field than any of the points listed above. Specifically, we would need to reconsider the value of journals. Perhaps the community's effort expended on those venues could be better spent on running better conferences?

8 Conclusions

The motivation of this work is that researchers should be able to explore software engineering, however their whims guide them. If the current structure of our SE conferences and journals inhibit that free exploration, then that structure should be changed. As described above in the section on *Recommendations*(§7), we think that several such changes are now justifiable.

To the best of our knowledge, this paper is the largest study of the SE literature yet accomplished (where "large" is measured in terms of number of papers and number of years). Here, text mining methods were applied to 35,391 documents written in the last 25 years from 34 top-ranked SE venues. These venues were divided, nearly evenly, between conferences and journals.

An important aspect of this analysis is that it is fully automated. Such automation allows for the rapid confirmation and updates of these results, whenever new data comes to hand. To achieve that automation, we used a stable topic modeling technique, LDADE, that fully automates parameter tuning in LDA. Without LDADE, engineers must use their judgment to set the tuning parameters of LDA. That approach means the resulting topics are sensitive to those tuning choices and, as discussed in §2.1.2, that the generated topics are unstable (i.e. prone to large changes, just by shuffling the input ordering of the data).

Finally, to repeat a comment from the introduction, the professional bodies that oversee our conferences and journals should create standing committees which, on an annual basis, generate reports like this paper about the state-of-play within SE publications. Such committees could offer data-driven recommendations about how to better manage our conferences and journals.

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