From Academia to Software Development: Publication Citations in Source Code Comments

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Abstract—Academic publications have been evaluated with the impact on research communities based on the number of citations. On the other hand, the impact of academic publications on industry has been rarely studied. This paper investigates how academic publications contribute to software development by analyzing publication citations in source code comments in open source software repositories. We propose an automated approach of detecting academic publications based on Named Entity Recognition, and achieve 0.90 in $F_1$ as detection accuracy. We conduct a large-scale study of publication citations with 319,438,977 comments collected from active 25,925 repositories written in seven programming languages. Our findings indicate that academic publications can be knowledge sources of software development, and there can be potential issues of obsoleting knowledge.

I. INTRODUCTION

How has “literate programming”, a programming paradigm proposed by Donald Knuth [1], made impact on software development? Although the paper [1] has been referenced by more than 2,100 academic papers1, can we see the impact on the real world programming? Similar to publication citations in academic papers, we observed that developers also reference academic publications to implement code. When we search the keyword “literate programming” in a source code search engine searchcode2, we can find the comment in a Java source file3 as shown in Figure 1. From Vol. 30, No. 7 in 1987 to Vol. 33, No. 3 in 1990, there were columns of “Literate Programming” in the Communications of ACM, and the above-mentioned code comment was written based on one of such articles [2].

In this work, we study publication citations in source code comments, which has not been well known. Publication citations in academia can be considered as a function in scientific communication among texts, as an indicator of reward in the science system, and as the collective character of scientific achievements [3]. Since software developers likely to reference academic publications as explicit knowledge sources to implement code, these citations can be considered to be knowledge transferring from academia to practice. The significance of this work is related to software documentation [4] from the perspective of knowledge sharing [5], [6]. For improving documentation and mitigating potential issues of obsoleting knowledge, understanding publication citations in software development is necessary and important.

This work is related to research on source code comments in terms of software documentation. Source code comment have been found to document personal and team tasks [7] and technical debt [8]. A recent study of links in source code comments revealed that comments are used to express background meta information, source code context information, and technical debt, with external sources via links [9]. Similar to links, referencing academic publications indicates external sources to explain associated code. However, to the best of our knowledge, publication citations in source code comments have not been studied comprehensively so far, hence there is a lack of knowledge on what kinds of academic achievements are referenced to develop software. To address this lack of knowledge, we conduct an empirical study to explore publication citations in source code comments.

Considering the detection of publication citations in source code comments as the task of information extraction, there are mainly three challenges. First, there is no explicit keywords to search. For link identification, the regular expression /http:S+/ can be used to identify links in text [9]. However, we cannot prepare such regular expressions to identify publication citations because of nonexistence of common words and patterns. Second, referencing publications in source code comments are written in free format and can appear anywhere. Since there is no rule for publication citations in source code comments, developers freely express references, such as omitting titles and other entities, and presenting with the \textit{BibTex} style, which makes it difficult to apply heuristics in parsing citations in papers [10]. The third challenge is the barrenness of the existence of publication citations. In the research on self-admitted technical debt, several machine learning approaches have been proposed to detect comments indicating self-admitted technical debt [11]–[13]. These approaches are based on supervised classification utilizing large amount of labeled data. Since there are not many comments referencing publications (we estimated less than 0.01% in all comments in our studied data), it is difficult to prepare enough

12,123 citations. Google Scholar: accessed Apr. 2019.
2searchcode: https://searchcode.com/, accessed Apr. 2019.
3openesb-components/ojc-core/component-common/xmlbeans/xbean-src/2.3.0/xmlbeans/test/tools/src/tools/util/Diff.java
data for training.

Our initial trial for automating detection with supervised classification, that is, classifying comments with citations or not, did not work well due to these difficulties. We also tried preliminary manual investigation by using public code search services. However, manual investigation is not scalable and the results can be biased.

To conduct a large-scale empirical study, by considering challenges in information extraction, we develop an approach of detecting publication citations in source code comments based on Named Entity Recognition (NER) [14]. By identifying publication-related named entities, such as authors, titles, journal names, years, etc., we infer the existence of publication citations. A model trained with manually annotated publication citations in comments was used to detect publication citations from 319,438,977 distinct comments in active software development projects written in seven programming languages. From manual validation in a statistically representative sample from all the comments we detected, we obtained 0.90 in F1 for detecting publication citations.

We find in the detected publication citations that not only one publication but multiple publications are referenced in a comment, “ACM TRANSACTIONS on MATHEMATICAL SOFTWARE” and “COMMUNICATION of the ACM” are the most referenced journals, publications in 1990s and 2000s are frequently referenced. We also find a potential issue of referencing older publications for knowledge obsolescence.

In summary, the contributions of this paper are three-fold:

- proposal of automated detection of publication citations in source code comments based on Named Entity Recognition,
- a large-scale and comprehensive study of publication citations in active software development projects written in seven programming languages, and
- an analysis of detected publication citations to understand knowledge transferring from academia to software development.

II. PRELIMINARY MANUAL INVESTIGATION

We started manual investigation in 2013 using a public code search service for OSS, Ohloh, provided by Black Duck Software at that time. It covered around 80 thousands C projects and 70 thousands Java projects. Using the code search service, the third author searched 50 journal names in C and Java source code, then manually validated publication citations. Targeted journals are selected as top 50 citations. Targeted journals are selected as top 50

| journal                                      | C | Java |
|----------------------------------------------|---|------|
| COMMUN ACM                                  | 78| 52   |
| ACM T MATH SOFTWARE                         | 78| 23   |
| IEEE COMPUT GRAPH                           | 16| 1    |
| ACM T GRAPHIC                               | 9 | 11   |
| ACM T PROGR LANG SYS                        | 11| 4    |
| J ACM                                       | 6 | 7    |
| ACM COMPUT SURV                             | 2 | 6    |
| SIAM J COMPUT                               | 1 | 6    |
| IEEE T SOFTWARE ENG                         | 2 | 5    |
| IEEE T SYST MAN CY A                        | 3 | 4    |
| ACM T COMPUT SYST                           | 2 | 2    |

In 2016 the fourth author again manually investigated publication citations of COMMUNICATIONS of the ACM as the most popular journal, using the public code search service searchcode with a query “cacm”. Data sources of searchcode come from Bitbucket, GitHub, Google Code, Sourceforge, GitLab and so on. Various programming languages are also covered. Table II shows frequently referenced papers in decades. In this investigation, five programming languages were targeted, that is, C, C++, C#, Java, and Python, to see how papers are referenced in different languages. We found that although the majority of referencing comments appeared in C source code, other languages also referenced academic publications. In addition, it is revealed that various papers in several decades had been utilized to implement code from 1950s to 2000s, which may infer the risk of obsoleting knowledge and code, especially for code referencing older publications.

From our manual investigation, we could clarify publication

5https://github.com/svn2github/cytoscape/blob/a3d9f63db44ec49942027ca91ecace6fa920e195/cplugins/trunk/agilent/kuchinsky/infolvis_0.9beta/src/infolvis/tree/visualization/nodelink/RTLayout.java#L25

6https://github.com/sba1/ontologizer/blob/62765f4c54d42daae999e480e7ef50bb510f5fc8/ontologizer.grappa/src/main/java/att/grappa/Grappa.java#L13

* This program is intended to be pedagogic. Specifically, this program was * the basis of the Literate Programming column which appeared in the * Communications of the ACM (CACM), in the June 1989 issue (32, 6, * 740–755).
In addition, choosing search queries can make results biased. Since code search runs on predetermined data sources, we cannot control criteria for selecting software to be analyzed. Empirical studies using code search services have concerns. The investigation does not scale; we cannot conduct large-scale studies. Manual collection procedure, and named entity recognition in brief.

We describe an overview of our study approach, data collection procedure, and named entity recognition in brief.

### III. STUDY SETUP

We consider the detection of publication citations in source code comments as the task of Named Entity Recognition (NER) [14]. We try detecting publication citations by identifying sets of publication-related named entities, such as authors, titles, journal names, years, and so on. For our empirical study, we collect a large amount of source code comments based on our criteria.

We describe an overview of our study approach, data collection procedure, and named entity recognition in brief.

#### A. Overview

Figure 2 presents an overview of our large-scale study of publication citations in source code comments, which consists of three components: training an NER model with manually annotated citations in specific comments (Section IV), evaluation of publication citation detection in a large amount of comments (Section V), and analysis of detected citations (Section VI).

#### B. Data Collection

Source code comments were collected with the same procedure in the previous study [9], which had targeted active software development repositories on GitHub written in common programming languages, that is, C, C++, Java, JavaScript, Python, PHP, and Ruby. Those 7 languages are considered to be common since they had been consistently ranked in the top 10 languages on GitHub in recent 10 years [15]–[17].

| decade | rank | paper | # code citations |
|--------|------|-------|-----------------|
| 1950s  | 1    | D. L. Shell, A high-speed sorting procedure (1959) | 2 (C 1, Java 1) |
| 1960s  | 1    | Robert L. Smith, Algorithm 116: Complex division (1962) | 21 (C 19, Python 2) |
|        | 2    | Immo O. Kerner, Algorithm 283: Simultaneous displacement of polynomial roots if real and simple (1966) | 15 (C 14, Java 1) |
|        | 3    | Robert G. Tanzen, Algorithm 199: conversions between calendar date and Julian day number (1963) | 8 (C 6, C++ 2) |
|        | 4    | G. Marsaglia, Generating discrete random variables in a computer (1963) | 6 (C 3, Java 3) |
|        | 5    | Paul Friedland, Algorithm 312: Absolute value and square root of a complex number (1967) | 5 (C 5) |
| 1970s  | 1    | Jay Earley, An efficient context-free parsing algorithm (1970) | 29 (Python 29) |
|        | 2    | J. P. Chandler and W. C. Harrison, Remark on algorithm 201 [M1]: shellsort (1970) | 11 (C 11) |
|        | 3    | J. H. Ahrens and U. Dieter, Computer methods for sampling from the exponential and normal distributions (1972) | 8 (C 6, C++ 2) |
|        | 4    | Alfred V. Aho and Margaret J. Corasick, Efficient string matching: an aid to bibliographic search (1975) | 8 (C 8) |
|        | 4    | Jack Bresenham, A linear algorithm for incremental digital display of circular arcs (1977) | 6 (C 6) |
|        | 5    | R. C. H. Cheng, Generating beta variates with nonintegral shape parameters (1978) | 6 (C 5, C++ 1) |
|        | 5    | Michael A. Malcolm, Algorithms to reveal properties of floating-point arithmetic (1972) | 5 (C 3, C++, 1, Java 1) |
|        | 5    | W. Morven Gentleman and Scott B. Marovich, More on algorithms that reveal properties of floating point arithmetic units (1974) | 5 (C 3, C++, 1, Java 1) |
|        | 5    | W. R. Franta and Kurt Maly, An efficient data structure for the simulation event set (1977) | 5 (C 5) |
| 1980s  | 1    | E. R. Fiala and D. H. Greene, Data compression with finite windows (1989) | 72 (C 72) |
|        | 2    | S. K. Park and K. W. Miller, Random number generators: good ones are hard to find (1988) | 42 (C 25, C++ 13, C#, 2, Java 1, Python 1) |
|        | 3    | Reinhold P. Weicker, Dhrystone: a synthetic systems programming benchmark (1984) | 36 (Python 30, C 4, C++, 2) |
|        | 4    | Per-Ake Larson, Dynamic hash tables (1988) | 13 (C 11, C++, 1, Java 1) |
|        | 5    | Richard J. Cichelli, Minimal perfect hash functions made simple (1980) | 8 (C 8) |
|        | 5    | J. H. Ahrens and U. Dieter, Generating gamma variates by a modified rejection technique (1982) | 8 (C 4, C++, 2, Java 2) |
|        | 5    | Ian H. Witten, Radford M. Neal, and John G. Cleary, Arithmetic coding for data compression (1987) | 5 (C 7, C++, 1) |
| 1990s  | 1    | Bala R. Vatti, A generic solution to polygon clipping (1992) | 15 (C++, 11, C# 4) |
|        | 2    | Peter K. Pearson, Fast hashing of variable-length text strings (1990) | 10 (C 7, C++, 3) |
|        | 3    | William Pugh, Skip lists: a probabilistic alternative to balanced trees (1990) | 8 (C 7, Python 1) |
|        | 4    | David F. Carta, Two fast implementations of the “minimal standard” random number generator (1990) | 7 (C 2, C++, 5) |
|        | 5    | Edward A. Fox, Lenwood S. Heath, Qi Fan Chen, and Amjad M. Daoud, Practical minimal perfect hash functions for large databases (1992) | 4 (C 3, Java 1) |

| 2000-  | 1    | George Marsaglia, Seeds for random number generators (2003) | 1 (C++, 1) |

**TABLE II:** Frequently referenced papers in Communications of the ACM in decades
Active software development repositories were selected from the GHTorrent datasets\(^7\) [18] with the following criteria [9]: (i) more than 500 commits (the same threshold used in previous work [19]), and (ii) at least 100 commits in the most active two years (to remove long-term less active projects and short-term repositories, which may not be software development projects [20]).

Table III shows the total number of collected repositories per language and in total. From the collected repositories, code comments were extracted in the HEAD commits with the tool [21]\(^8\) used in the previous study [9]. Although there are many duplicate comments mainly because of code reuses, we obtained distinct code comments for each language. As seen in Table III, we have more than 300 million distinct code comments with the large amount of comments in C code. From those comments, special characters (‘\n’, ‘\’, ‘\’, ‘\’; ‘\#’, ‘!’) were removed as preprocessing.

\(^7\)MySQL database dump 2018-04-01 from http://ghtorrent.org/downloads.html.
\(^8\)Comment Lister. https://github.com/takashi-ishio/CommentLister

Compared to using searchcode, our dataset consists of only source code comments without duplicates only from active repositories, but is limited to seven programming languages only from GitHub.

\(C.\) Named Entity Recognition

Named Entity Recognition (NER) is the task of identifying named entities in unstructured text, such as name of a person, location, organization, time, etc. [14]. In fields of Natural Language Processing (NLP) and Information Retrieval (IR), NER is used in many areas to help in answering real-world questions, summarizing text, and translating. We adopt Spacy\(^9\) [22] for as a NER tool. Spacy is a module written in Python and Cython for NLP to train the NER model\(^10\). It provides some features that are commonly used in NLP projects to identify the named entities, such as tokenization, lemmatisation, part-of-speech tagging, entity recognition, etc. One benefit of using spacy module is having better performance comparing to NLTK, especially on tokenization and part-of-speech tagging tasks [23].

When using Spacy for NER, we can make use of publicly available pre-trained statistical models\(^11\). We selected \texttt{en\_core\_web\_sm}, a model trained on OntoNotes 5. OntoNotes 5 is the final release of the OntoNotes project, which intends to annotate a large corpus comprising various genres of text (news, conversational telephone speech, weblogs, usenet newsgroups, broadcast, talk shows) [24]. Several entity types are supported in the model, such as person, organization, date, and so on.\(^11\)

\(^9\)https://spacy.io
\(^10\)https://spacy.io/models/en
\(^11\)https://spacy.io/api/annotation#named-entities
TABLE IV: Comments including keywords ACM and IEEE

|          | ACM  | IEE  | sum   |
|----------|------|------|-------|
|          | 5,521| 16,682| 22,203|
| group A  | all  | 4,372| 7,656 | 12,028|
|          | sample| 353  | 366   | 719   |
|          | cite  | 175  | 92    | 267   |
|          | none  | 178  | 274   | 452   |
| group B  | all  | 1,149| 9,026 | 10,175|
|          | sample| 288  | 369   | 657   |
|          | cite  | 1    | 4     | 5     |
|          | none  | 287  | 365   | 652   |
| train & validate | sum  | 641  | 735   | 1,376 |
|          | cite  | 176  | 96    | 272   |
|          | none  | 465  | 639   | 1,104 |

IV. MODEL TRAINING

To apply NER for identifying publication-related named entities, we prepare new entity types and annotate some comments with them. Those annotated comments are used to train an existing pre-trained model.

A. Filtering and Sampling

For preparing data to be used to train our model, comments that contain publication citations are needed. From the entire 319,438,977 comments, we first collect comments that include popular association names, ACM and IEEE, since there can be various journals or conferences related to those associations to be referenced in source code comments as seen in Section II. As seen in Table IV, we obtained 5,521 distinct comments for ACM and 16,682 distinct comments for IEEE.

We divide those comments into two groups A and B, as a group of comments that are prone to contain publication citations and a group of comments that are not prone to contain them. The first author manually investigated those comments and decided criteria for this grouping. For comments with ACM, group B comments were identified with a keyword “@acm.org” as they tend to contain only such email addresses. The other 4,372 comments were summarized in group A. Similarly “IEEE.org” and “IEEE STD” were used as keywords to select comments with IEEE for group B. To identify comments with IEEE Standards and put them into group B, numbers 488, 754, 802, 854, 1003, 1076, 1149, 1275, 1284, 1355, and 1363, following “IEEE’ ’ (space), IEEE- or IEEE_.. For comments with IEEE, there are 9,026 comments in group B and 7,656 comments in group A.

From those four groups (two groups in ACM and IEEE), we obtained a statistically representative sample for each group. The required sample size was calculated so that the ratio of publication citations would generalize to all comments in the same group with a confidence level of 95% and a confidence interval of 5%.

B. Annotation

The first author manually investigated all 1,376 samples (353+366+288+369) and identified 272 comments with publication citations (175+92+1+4). Publications found in group B are not related to ACM nor IEEE, but those associated comments include “@acm.org”, “IEEE 802”, or “ieee.org”.

For identified 272 comments including publication citations, we annotated the following publication-related entities (each number presents the number of appearance in all citations in the comments): author (888), title (408), year (407), booktitle_or_journal (353), pages (251), volume (234), number (165), month (116), url (92), publisher (74), address (31), doi (27), isbn (7), and issn (2). Since individual authors are annotated separately, the number of author entities is the largest. Book titles for conferences and journal names are integrated into one entity booktitle_or_journal. For volume, number, and pages, some citations contain keywords, such as ‘Vol.’, ‘No.’, and ‘pages’. In such cases, these keywords were included for entities as well as numbers.

C. Validation and Training

To evaluate the effectiveness of NER with our annotated comments for publication citation detection, we conduct 10-fold cross-validation with all 1,376 samples shown in Table IV. All comments were randomly divided into 10 subsamples, and 9 were used for training and the remaining were used for testing. The cross-validation process is repeated 10 times. For testing, prepared publication-related entities were identified with the trained models.

For comments with citations, there were 11.1 identified entities in average. However, there were only 1.2 identified entities in average for comments without citations. With the set of identified entities in comments, the detection performance was measured with precision, recall, and $F_1$. From the all possible combinations with high $F_1$ (top 10), the combinations sorted by precision are shown in Table V. For these combinations, we achieved high $F_1$, that is, more than or equal to 0.87. Since we try detecting publication citations in a large amount of comments, we consider precision is important. The combination of ‘author’, ‘title’, ‘year’, and ‘booktitle_or_journal’ is found to be the highest precision 0.99.

From this result we consider NER with our annotated comments works well to detect publication citations, hence we train the model with all 272 annotated comments for large-scale comments.

V. DETECTION EVALUATION

In this section, we present the detection of publication citations in a large amount of source code comments and

TABLE V: Accuracy with the combination of detected entities

| set of entities | precision | recall | $F_1$ |
|----------------|-----------|--------|-------|
| author, title, year, booktitle_or_journal | 0.99 | 0.78 | 0.87 |
| title, year, booktitle_or_journal | 0.96 | 0.81 | 0.88 |
| author, year, booktitle_or_journal | 0.96 | 0.80 | 0.87 |
| author, title, booktitle_or_journal | 0.95 | 0.83 | 0.89 |
| year, booktitle_or_journal | 0.92 | 0.84 | 0.88 |

12https://www.surveystem.com/sscalc.htm
TABLE VI: Detected publication citations and their statistically representative sample

| # | % |
|---|---|
| all comments | 319,438,977 | 100% |
| comments satisfying the detection criteria | 11,724 | 0.0037% |
| sample from the above 11,274 comments | 372 | 100% |
| cite | 305 | 82% |
| none | 67 | 18% |

discuss our manual evaluation in a statistically representative sample of the detected publication citations.

A. Automated Detection

The trained model prepared in Section IV was used to detect publication citations from the all distinct 319,438,977 source code comments. To decrease incorrectly detected comments, the set of the four entities (author, title, year, and booktitle_or_journal), which shows the highest precision shown in Table V, was used for the detection criterion to be included.

Different from the small samples used for the validation in Section IV, with the large amount of data, we found that the criterion only with the four entities was not good enough to detect accurately. Some larger source code comments incorrectly found to include the four types of entities in separate parts of the comments, which should not be publication citations. To ignore such misidentification, we measure the distances in pairs of closest detected entities, and remove source code comments with more than 10 distances (including spaces, characters, and special characters) for the largest gaps.

As shown in Table VI, we obtained 11,724 distinct comments (C 3,696, C++ 3,371, Java 2,415, JavaScript 197, Python 1,994, PHP 30, and Ruby 21), which is only 0.0037% from the all comments. Although our detection criteria can miss some comments with publication citations, we estimate that the percentage of comments with publication citations will not exceed 0.01%.

B. Sampling and Evaluation

Since investigating 11,724 comments manually is not practical, we prepared a statistically representative sample, so that the conclusions would generalize to all 11,724 identified comments. The sample size was again calculated with a confidence level of 95% and a confidence interval of 5, then we obtained 372 comments. The second author investigated 372 comments and found that 305 comments actually include publication citations. We obtained the highest F1 0.90, which seems to be convincingly high.

| correct (%) | partially cor. | incor. |
|-------------|----------------|-------|
| author | 237 (78%) | 63 | 5 |
| title | 233 (76%) | 53 | 19 |
| year | 269 (88%) | 36 | 0 |
| booktitle_or_journal | 233 (76%) | 38 | 34 |

Entity identification accuracy. Although we could detect publication citations accurately, it is not clear how appropriate identified entities are. The second author again manually validated the four types of entities in 305 comments that include publication citations. In a comment, there can be multiple entities for the same type, such as multiple authors for one publication, or because of multiple publications. If all entities in the same types are appropriate, we consider correct. If all entities in the same types are inappropriate, we consider incorrect. We consider partially correct for the others.

Table VII summarizes the number of comments with the above categories. As expected, year is the most correctly identified entity, accounting for 88%. At least one year entity was identified correctly in all comments. The other three entities achieve similar accuracy of correct, accounting for 76-78%. Considering partially correct, part of author entities were prone to be identified accurately in most comments. Among the four entity types, the entity booktitle_or_journal is found to be relatively difficult to identify.

Figure 4 is a part of a source code comment with actual publication citation we detected. In this citation, publication title is not presented. Although author and year were identified almost correctly, inappropriate entities were identified as title and booktitle_or_journal. However, since the four entity types were included and the largest distance is smaller than 10, this publication citation was detected. Similar to this example, we could detect publication citation correctly even

13”Becker, P. J.” is one author entity.
Fig. 4: A successfully detected publication citation that does not include title. The actual title is “Extinction within the limit of validity of the Darwin transfer equations. I. General formalism for primary and secondary extinction and their applications to spherical crystals”

TABLE VIII: The number of publications in a comment

| # publications | # comments | %  |
|----------------|------------|----|
| 1              | 176        | 58%|
| 2              | 93         | 30%|
| 3              | 21         | 7% |
| 4              | 8          | 3% |
| 5              | 6          | 2% |
| 6              | 1          | 0% |
| sum            | 305        | 100%|

Figure 5 is an example of comments that were incorrectly detected as publication citation. Similar to this example, parts of comments that include person names and years were prone to be detected. Compared to the performance of the detection of publication citations, results of identified entities were relatively lower. Improving our detection criteria and introducing automated validation processes should be promising future directions.

VI. Citation Analysis

In this section, we present our findings in the analysis of the detected publication citations in source code comments.

A. Citation Statistics

To understand a common practice of publication citations in source code comments, we investigate the number of publications referenced in a source code comment. Table VIII summarizes the groups of comments categorized based on the number of referenced publications in a source code comment. From the sample of 305 comments with publication citations, 58% of comments referenced only one publication. Interestingly, more than 40% of comments referenced multiple publications. At most six publications were referenced in one comment. It is revealed that not only single publications but multiple publications can be made use of as the knowledge sources of implementing source code.

B. Popular Publications

In the collected large amount of source code comments in the wild, which publications had been frequently referenced? From 11,274 comments that satisfy the detection criteria, all the entities identified as title were collected. Those entities were sorted by the number of comments that include the entities. The entities that appear more than or equal to 20 times were validated manually, and 93 actual titles were obtained. Table IX shows the top 20 most referenced publications cited in source code comments. The accurate authors, years, and booktitles or journal names were summarized from reliable sources. We found various types of publications in the top 20, that is, 10 journal articles, 3 conference papers, 3 books, 2 technical reports, 1 Request for Comments (RFC), 1 PhD thesis. Such result demonstrates the effectiveness of our NER approach, as our preliminary manual investigation with predetermined keywords (Section II) could not detect various publications types. Table IX also presents the number of citations in academia, based on Google Scholar accessed Apr. 2019. Although some publications have lower impacts in academia, they can higher impact in software development.

Table X summarizes the number of distinct referenced publications from the 93 popular publications for their journals or conferences. ACM TRANSACTIONS on MATHEMATICAL SOFTWARE and COMMUNICATION of the ACM were found to be the most referenced journals, which is similar to Table I.

C. Publication Years

To better understand academic knowledge sources used for software development, publication years in the 305 sample were analyzed. For those actual publication citations in the 305 comments, the second author manually confirmed publication years. As seen in Table VIII, there can be multiple publication years in a comment. Figure 6 shows the histogram of appeared publication years. Although the number of publications in 2010s is not large, not so old publications were referenced.
TABLE IX: Top 20 referenced publications

| rank | publication                                                                 | # code citations | # paper citations |
|------|------------------------------------------------------------------------------|------------------|------------------|
| 1    | C. Loeffler, A. Ligtenberg, G.S. Moschytz, Practical fast 1-D DCT algorithms with 11 multiplications, Proceedings of 1989 International Conference on Acoustics, Speech, and Signal Processing (1989) | 146 (C 105, C++ 19, Java 1, JavaScript 21) | 1,088 |
| 1    | S. Reiter, A. Vogel, I. Heppner, M. Rupp, G. Wittum, A massively parallel geometric multigrid solver on hierarchically distributed grids, Computing and Visualization in Science (2013) | 146 (C++ 146) | 31 |
| 3    | S. Tomov, J. Dongarra, Accelerating the reduction to upper Hessenberg form through hybrid GPU-based computing, University of Tennessee Computer Science Technical Report (2009) | 75 (C++ 75) | 23 |
| 4    | V.I. Lebedev, D.N. Laikov, A quadrature formula for the sphere of the 131st algebraic order of accuracy, Doklady Mathematics (1999) | 71 (C++ 71) | 463 |
| 5    | R. Sedgewick, Algorithms, 2nd Edition, Addison-Wesley (1988) | 67 (C 61, C++ 6) | 5,523 |
| 5    | E.R. Fiala, D.H. Greene, Data compression with finite windows, Communications of the ACM (1989) | 67 (C 61, C++ 6) | 295 |
| 7    | P. L'Ecuyer, Maximally equidistributed combined Tausworthe generators, Mathematics of Computation (1986) | 63 (C 59, C++ 4) | 308 |
| 8    | M. Matsumoto, T. Nishimura, Mersenne twister: a 623-dimensionally equidistributed uniform pseudo-random number generator, ACM Transactions on Modeling and Computer Simulation (1998) | 57 (C 56, C++ 14, Java 19) | 6,207 |
| 8    | P. L'Ecuyer, Tables of maximally equidistributed combined LFSR generators, Mathematics of Computation (1999) | 55 (C++ 2, JavaScript 53) | 1,352 |
| 10   | J.P. Snyder, Map projections—A working manual, U.S. Geological Survey Professional Paper (1987) | 55 (C++ 2) | 655 |
| 10   | P. Deutsch, DEFLATE compressed data format specification version 1.3, RFC 1951 (1996) | 55 (C 51, C++ 4) | 81 |
| 11   | J.M. Robson, Bounds for some functions concerning dynamic storage allocation, Journal of the ACM (1974) | 51 (C 44, C++ 7) | 587 |
| 12   | J.C.R. Bennett, H. Zhang, Hierarchical packet fair queuing algorithms, IEEE/ACM Transactions on Networking (1997) | 50 (C 50) | 58 |
| 13   | I. Stoica, H. Abdel-Wahab, Earliest eligible virtual deadline first: A flexible and accurate mechanism for proportional share resource allocation, Technical Report (1995) | 50 (C 50) | 58 |
| 14   | M. Matsumoto, Y. Kurita, Twisted GFSR generators II, ACM Transactions on Modeling and Computer Simulation (1994) | 49 (C 47, C++ 2) | 221 |
| 14   | M. Matsumoto, Y. Kurita, Twisted GFSR generators, ACM Transactions on Modeling and Computer Simulation (1992) | 47 (C 47) | 200 |
| 17   | S. Muchnick, Advanced compiler design and implementation, Academic Press, Morgan Kaufmann Publishers (1997) | 43 (C 43) | 3,751 |
| 17   | R.J. Gowersk, M. Linke, J. Barnoud, T.J.E. Reddy, M.N. Melo, S.L. Seyler, J. Domanski, D.L. Dotson, S. Buchoux, I.M. Kenney, O. Beckstein, MDAnalysis: a Python package for the rapid analysis of molecular dynamics simulations, Proceeding of 15th Python in Science Conference (2016) | 43 (Python 43) | 68 |
| 17   | Y. Wang, I.H. Witten, Modeling for optimal probability prediction, Proceedings of 19th International Conference on Machine Learning (2002) | 43 (Java 43) | 52 |
| 17   | Y. Wang, A new approach to fitting linear models in high dimensional spaces, PhD Thesis, University of Waikato, NZ (2000) | 43 (Java 43) | 45 |

Most publications referenced in source code comments had been published in 1990s and 2000s.

TABLE X: Frequently referenced journals or conferences

| rank | journal or conference | # papers |
|------|-----------------------|----------|
| 1    | ACM T MATH SOFTWARE   | 7        |
| 2    | COMMUN ACM            | 4        |
| 3    | ACM T MODEL COMP SIM  | 3        |
| 3    | IEEE ACM T NETWORK    | 3        |
| 3    | INT CONF MACHINE LEARNING | 3    |
| 3    | MATH COMP             | 3        |
| 7    | ACM SIGCOMM           | 2        |
| 2    | ADDISON-WESLEY        | 2        |
| 2    | CONF UNC ARTIFICIAL INTELLIGENCE | 2    |
| 2    | EURO CONF MACHINE LEARNING | 2    |
| 2    | IEEE INFOCOM          | 2        |

Fig. 6: Frequency of citations per decade from sample
D. Potential Issues Related to Knowledge Sources

Regarding publication citations in source code comments, are there any potential issues? From the top 20 referenced publications shown in Table IX, we observed three related papers, that is, Twisted GFSR generators by Matsumoto and Kurita (1992 and 1994) [25], [26] and Mersenne twister by Matsumoto and Nishimura (1998) [27]. The Mersenne twister is extended from the previous Twisted GFSR [27], and is the industry-standard algorithm for generating random samples [28]. Programs of Mersenne twister implemented by the authors are provided

Considering Mersenne twister is improved from Twisted GFSR and is the industry-standard, referencing the paper of Mersenne twister to implement the algorithm seems to be appropriate, instead of (only) referencing the older papers of Twisted GFSR. For the number of citations in papers, only the paper of Mersenne twister has obtained a large amount of citations (more than 6,200). However, for the citations in code comments, the differences in the number of citations among the three papers are small.

We searched comments that contain the paper title “Twisted GFSR generators” in all comments including duplicates from the all 2,482 C repositories (Table III). In total 142 comments were obtained. All the comments have the same contents, which should be the results of code reuses. Because of several modifications for different typos, variations in text exist, and result in 47 distinct comments. All the comments reference both Twisted GFSR papers [25], [26] but do not reference the Mersenne twister paper [27], although their associated code are for random number generation. It seems that an original developer implemented code based on Twisted GFSR and the code has been reused in many active repositories. If developers are not intentionally avoiding the Mersenne twister algorithm, there seems to be an issue of obsoleting knowledge. If those repositories update to Mersenne twister, there could be practical impacts for developers and users.

E. Online Appendix

Our online appendix contains our programs to detect publication citations and the result of identified titles. The appendix is available at http://tinyurl.com/citation-in-comment.

VII. Recommendations

Our findings can be summarized into recommendations for software developers and software engineering researchers.

Our recommendation for software developers is:

- Be aware of state-of-the-art academic achievements to maintain and improve source code. Past publications might turn out to be buggy, or new algorithms can overcome older algorithms.

We can also consider future work with the following possible challenges.

- Further studies of clues to intentions of developers in source code comments. As previous studies revealed source code comments contain different types of clues to developers’ intentions, such as personal and team tasks [7], technical debt [8], and external information sources via links [9]. Publication citations can be another clues to developers’ knowledge sources. Deepening the understanding of such clues or studying different types of clues are required to further understand developers’ intentions and their code.

- Tool support for knowledge transferring from academia to software development. Although paying attention to recent academic achievements can be a good custom for developers, it is not practical to cover various research topics related to large amount of code resources. Tools or systems to support knowledge transferring and maintain knowledge-code chains could be practically useful.

VIII. Threats to Validity

Several threats to the construct validity exist in our study. Since our detection criteria require four types of entities, publication citations that lack those types could not be detected and were ignored in our citation analysis. The previous study of links in source code comments reported that there are cases referencing academic publication only with links [9]. Those publication citations cannot be detected with Named Entity Recognition.

Threats to the external validity exist in our data preparation. Since our dataset comes only from GitHub, we cannot generalize our findings to industry nor free/libre and open source software in general. Moreover, although we targeted common seven programming languages, different programming languages can have different results.

To minimize the threats to reliability, we make our dataset publicly available. We provide our data in an online appendix including our source code files and identified titles (see Section VI-E).

IX. Related Work

Since the scientific citation index was proposed by Garfield [29], the study of academic paper citations has cut the boundaries of classical indexing of subject and become one of the importance in reference libraries. Many previous works focused on the citing paper analysis that has been implemented to academic evaluation including the authors’ names, journals, organizations etc. Paper citation is commonly studied in various topics, such as categorizing the citation profiles [30], and analyzing how the scholars cited papers [31], [32].

Chakraborty et al. [30] present an analysis that characterizes the important categories of scientific citations in computer science. The authors built a model for classifying papers into temporary and perennial, so that the behavior of numerous citation profiles can be replicated. The model showed the citation structures from diverse categories that indicates the similarity to the real data.
An investigation on citing behavior conducted by Bornmann and Daniel [31] reveals that the scientists motivation to cite references is not only for intellectual acknowledgement, but also other non-scientific factors, which is relevant indicator of the growth of citation number. It is even strengthened in a study on citation behavior prediction [32] that shown the number of citations in the future will increase linearly compared to the current number.

The bibliometric topics have also been investigated in several studies, for instance analyzing the reason of citing papers [33]–[35], evaluating the impact of academic papers [36] and analyzing the social network and the future trends of citations [37]. However, none of the related work provides a comprehensive study of paper citations in source code comments, which is the goal of this paper.

X. Conclusion
To understand the contribution of academic publications in software development, we (i) train a Named Entity Recognition model to automatically detect publication citations in source code comments; (ii) conduct a large-scale study with 319,438,977 distinct comments extracted from active 25,925 repositories written in seven languages; and (iii) perform a quantitative study of detected publication citations to understand knowledge transferring from academia to software development. Our study has shown that software development could not be separated from the achievements in academia. Based on this work that has clarified the activities of referencing publications in source code comments, there are many open avenues for future work: further studies of clues to intentions of developers in source code comments, and tool support for knowledge transferring from academia to software development, to name a few.

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