NLP4NLP+5: The Deep (R)evolution in Speech and Language Processing

Joseph Mariani1*, Gil Francopoulo2, Patrick Paroubek1 and Frédéric Vernier1

1 Université Paris-Saclay, CNRS, Laboratoire Interdisciplinaire des Sciences du Numérique, Orsay, France, 2 Tagmatica, Paris, France

This paper aims at analyzing the changes in the fields of speech and natural language processing over the recent past 5 years (2016–2020). It is in continuation of a series of two papers that we published in 2019 on the analysis of the NLP4NLP corpus, which contained articles published in 34 major conferences and journals in the field of speech and natural language processing, over a period of 50 years (1965–2015), and analyzed with the methods developed in the field of NLP, hence its name. The extended NLP4NLP+5 corpus now covers 55 years, comprising close to 90,000 documents [+30% compared with NLP4NLP: as many articles have been published in the single year 2020 than over the first 25 years (1965–1989)], 67,000 authors (+40%), 590,000 references (+80%), and approximately 380 million words (+40%). These analyses are conducted globally or comparatively among sources and also with the general scientific literature, with a focus on the past 5 years. It concludes in identifying profound changes in research topics as well as in the emergence of a new generation of authors and the appearance of new publications around artificial intelligence, neural networks, machine learning, and word embedding.

Keywords: speech processing, natural language processing, artificial intelligence, neural networks, machine learning, research metrics, text mining

INTRODUCTION

Preliminary Remarks

The global aim of this series of studies was to investigate the speech and natural language processing (SNLP), research area through the related scientific publications, using a set of NLP tools, in harmony with the growing interest for scientometrics in SNLP [refer to Banchs, 2012; Jurafsky, 2016; Atanassova et al., 2019; Goh and Lepage, 2019; Mohammad, 2020a,b,c; Wang et al., 2020; Sharma et al., 2021 and many more] or in various domains such as economics (Muñoz-Céspedes et al., 2021), finance (Daudert and Ahmadi, 2019), or disinformation (Monogarova et al., 2021).

The first results of these studies were presented in two companion papers, published in the first special issue “Mining Scientific Papers Volume I: NLP-enhanced Bibliometrics” of the Frontiers in Research Metrics and Analytics journal; one on production, collaboration, and citation: “The NLP4NLP Corpus (I): 50 Years of Publication, Collaboration and Citation in Speech and Language Processing” (Mariani et al., 2019a) and a second one on the evolution of research topics over time, innovation, use of language resources and reuse of papers and plagiarism within and across publications: “The NLP4NLP Corpus (II): 50 Years of Research in Speech and Language Processing” (Mariani et al., 2019b).

We now extend this corpus by considering the articles published in the same 34 sources over the past 5 years (2016–2020). We watched during this period an increasing interest for
machine-learning approaches for processing speech and natural language, and we wanted to examine how this was reflected in the scientific literature. Here, we therefore analyze these augmented data to identify the changes that happened during this period, both in terms of scientific topics and in terms of research community, reporting the results of this new study in a single article covering papers and authors’ production and citation within these sources, which is submitted to the second special issue “Mining Scientific Papers Volume II: Knowledge Discovery and Data Exploitation” of the Frontiers in Research Metrics and Analytics journal. We invite the reader to refer to the previous extensive articles to get more insights on the used data and developed methods. In addition, we conducted here the study of the more than 1 million total number of references, to measure the possible influence of neighboring disciplines outside the NLP4NLP sources.

**The NLP4NLP Speech and Natural Language Processing Corpus**

The NLP4NLP corpus\(^1\) (Mariani et al., 2019a) contained papers from 34 conferences and journals on natural language processing (NLP) and spoken language processing (SLP) (Table 1) published over 50 years (1965–2015), gathering about 68,000 articles and 270MWords from about 50,000 different authors, and about 325,000 references. Although it represents a good picture of the international research investigations of the SNLP community, many papers, including important seminal papers, related to this field, may have been published in other publications than these. Given the uncertainty of the existence of a proper review process, we did not include the content neither of workshops nor of publications such as arXiv\(^2\), a popular non-peer-reviewed, free distribution service and open-access archive created in 1991 and now maintained at Cornell University. It should be noticed that conferences may be held annually, may appear every 2 years (on even or odd years), and may also be organized jointly on the same year.

**The NLP4NLP+5 Speech and Natural Language Processing Corpus**

The NLP4NLP+5 corpus covers the same 34 publications up to 2020, hence 5 more years (2016–2020), which represents an addition in time of 10%. We preferred not to add new sources to facilitate the comparison between the situations in 2015 and 2020. However, we added in the present paper a Section Analysis of the Citation in NLP4NLP Papers of Sources From the Scientific Literature Outside NLP4NLP on the study of references to papers published in other sources than those of NLP4NLP. This new corpus also includes some articles published in 2015, which were not yet available at the time we produced the first NLP4NLP corpus. Some publications may no longer exist in this extended period (Table 1).

The extended NLP4NLP+5 new corpus contains 88,752 papers (+20,815 papers (+30%) compared with NLP4NLP), 85,138 papers if we exclude duplicates (such as papers published at joint conferences) and 84,006 papers after content checking (+20,649 papers), 587,000 references [+262,578 references (+80%)], 381 MWords [+111 MWords (+40%)], and 66,995 authors [+18,101 authors (+40%)]. The large increase in these numbers illustrates the dynamics of this research field.

To study the possible differences across different communities, we considered two different research areas, speech processing and natural language processing, and we attached the sources to each of those areas (Table 2), given that some sources (e.g., LREC, LRE, L&TC, MTS) may be attached to both research domains. We see that the number of documents related to speech is larger than the one related to NLP. We only considered the papers related to speech processing (named ICASSPS) in the IEEE ICASSP conference, which also includes a large number of papers on acoustics and signal processing in general.

The number of conference or journal events\(^3\) may largely vary, from 3 for Tipster to 46 for the Institute of Electrical and Electronics Engineers (IEEE)/Association for Computing Machinery (ACM) TASLP and the time span is also different, from 5 years for Tipster to 55 years for COLING. The number of papers in each source largely varies, from 82 papers for the ACM TSLP to 22,778 papers for the ISCA conference series.

**GLOBAL ANALYSIS OF THE CONFERENCES AND JOURNALS**

**Production of Papers Over the Years**

A total number of 88,752 documents have been published in the 34 sources over the years. If we do not separate the papers that were published at joint conferences, it reduces to 85,138 papers (Table 1), with a steady increase over time from 24 papers in 1965 to 5,430 in 2020 (Figure 1). This number fluctuates over the years, mainly due to the biennial frequency of some important conferences (especially LREC and COLING on even-numbered years). The largest number of papers ever has been published in 2020 (5,430 papers), comparable in a single year to the total number of papers (5,725 papers) published over the 25 initial years (1965–1989)!

The total number of papers itself still increases steadily at a rate which now stabilizes at about 6% per year (Figure 2), reaching 85,138 different documents as of 2020 (Figure 3).

**Data and Tools**

Most of the data are freely available online on the Association for Computational Linguistics (ACL) anthology website, and others are freely available in the International Speech Communication Association (ISCA) and Text Retrieval Conference (TREC) archives. IEEE International Conference on Acoustics, Speech and Signal Processing - Speech Track (ICASSP) and Transactions on Audio, Speech, and Language Processing (TASLP) articles have been obtained through the IEEE, and Language Resources and Evaluation (LRE) articles through Springer. For this study, we only considered the papers written in English and French. Most of the documents were available as textual data in PDF, whereas the eldest ones were only available as scanned images.

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\(^1\)http://www.nlp4nlp.org

\(^2\)https://arxiv.org/

\(^3\)We call “event” the holding of a conference or the publication of a volume of a journal.
and had to be OCRized, which resulted in a lower quality. The study of the authors, of the papers as well as of the papers cited in the references, is problematic due to variations in the same name (family name and given name, initials, middle initials, ordering, married name, etc.) and required a very tedious semi-automatic cleaning process (Mariani et al., 2014), and the same for the sources cited in the references. After a preprocessing phase, the metadata and contents are processed by higher level NLP tools, including a series of Java programs that we developed (Francopoulo et al., 2015a,b, 2016a).

**Overall Analysis**

**Authors’ Renewal and Redundancy**
We studied the authors’ renewal. Figure 4 clearly shows that the number of different authors increased a lot over the years, and especially in the recent years, in a similar way than the number of papers, to reach 66,995 authors in 2020.

The number of different authors on a year also globally increased over time (Figure 5), with an exceptional increase in the past 5 years (from 6,562 in 2015 to 13,299 in 2020). The number of new authors from one conference to the next similarly

### TABLE 1 | The NLP4NLP+5 corpus of conferences (24) and journals (10).

| Short name | # docs | Format | Long name | Language | Access to content | Period | # events |
|------------|--------|--------|-----------|----------|-------------------|--------|----------|
| acl        | 6,713  | Conference | Association for Computational Linguistics conference series | English | Open access* | 1979–2020 | 42 |
| acltslp    | 82     | Journal | ACM Transaction on Speech and Language Processing | English | Private access | 2004–2013 | 10 |
| alta       | 261    | Conference | Australasian Language Technology Association conference series | English | Open access* | 2003–2019 | 17 |
| anlp       | 278    | Conference | Applied Natural Language Processing | English | Open access* | 1985–2000 | 6 |
| cath       | 927    | Journal | Computers and the Humanities | English | Private access | 1966–2004 | 39 |
| cl         | 905    | Journal | American Journal of Computational Linguistics | English | Open access* | 1980–2020 | 41 |
| coling     | 5,091  | Conference | Conference on Computational Linguistics | English | Open access* | 1965–2020 | 24 |
| conll      | 1,124  | Conference | Computational Natural Language Learning | English | Open access* | 1997–2020 | 23 |
| csal       | 1,111  | Journal | Computer Speech and Language | English | Private access | 1986–2020 | 34 |
| eacl       | 1,139  | Conference | European Chapter of the ACL conference series | English | Open access* | 1983–2017 | 15 |
| emnlp      | 4,588  | Conference | Empirical methods in natural language processing | English | Open access* | 1996–2020 | 25 |
| hlt        | 2,219  | Conference | Human Language Technology | English | Open access* | 1986–2015 | 19 |
| iccaspns   | 10,971 | Conference | IEEE International Conference on Acoustics, Speech and Signal Processing - Speech Track | English | Private access | 1990–2020 | 31 |
| ijcnlp     | 2,047  | Conference | International Joint Conference on NLP | English | Open access* | 2005–2019 | 8 |
| inlg       | 4,015  | Conference | International Conference on Natural Language Generation | English | Open access* | 1996–2020 | 12 |
| isca       | 22,778 | Conference | International Speech Communication Association conference series | English | Open access | 1987–2020 | 33 |
| jep        | 739    | Conference | Journées d’Etudes sur la Parole | French | Open access* | 2002–2020 | 8 |
| lre        | 490    | Journal | Language Resources and Evaluation | English | Private access | 2005–2020 | 16 |
| lrec       | 6,920  | Conference | Language Resources and Evaluation Conference | English | Open access* | 1998–2020 | 12 |
| ltc        | 793    | Conference | Language and Technology Conference | English | Private access | 1995–2019 | 9 |
| modulad    | 232    | Journal | Le Monde des Utilisateurs de L’Analyse des Données | French | Open access | 1988–2010 | 23 |
| mts        | 906    | Conference | Machine Translation Summit | English | Open access* | 1987–2019 | 17 |
| muc        | 149    | Conference | Message Understanding Conference | English | Open access* | 1991–1998 | 5 |
| naacl      | 2,175  | Conference | North American Chapter of the ACL conference series | English | Open access* | 2000–2019 | 14 |
| paclic     | 1,352  | Conference | Pacific Asia Conference on Language, Information and Computation | English | Open access* | 1995–2018 | 23 |
| ranlp      | 521    | Conference | Recent Advances in Natural Language Processing | English | Open access* | 2009–2019 | 4 |
| sem        | 1,089  | Conference | Lexical and Computational Semantics / Semantic Evaluation | English | Open access* | 2001–2020 | 13 |
| speechc    | 1,087  | Journal | Speech Communication | English | Private access | 1982–2020 | 39 |
| tacl       | 307    | Journal | Transactions of the Association for Computational Linguistics | English | Open access* | 2013–2020 | 8 |
| tal        | 222    | Journal | Revue Traitement Automatique du Langage | French | Open access | 2006–2020 | 15 |
| tain       | 1,250  | Conference | Traitement Automatique du Langage Naturel | French | Open access* | 1997–2020 | 24 |
| taslp      | 7,387  | Journal | IEEE/ACM Transactions on Audio, Speech, and Language Processing | English | Private access | 1975–2020 | 46 |
| tipster    | 105    | Conference | Tipster Defense Advanced Research Projects Agency (DARPA) text program | English | Open access* | 1993–1998 | 3 |
| trec       | 2,199  | Conference | Text Retrieval Conference | English | Open access | 1992–2020 | 29 |
| Total incl. duplicates | 88,752 | | | | | 1965–2020 | 687 |
| Total excl. duplicates | 85,138 | | | | | 1965–2020 | 667 |

*Included in the ACL anthology:

### TABLE 2 | Sources attached to each of the two research areas.

| Research area | Sources | # Docs |
|---------------|---------|--------|
| NLP-oriented  | acl, alta, anlp, cath, cl, coling, conll, emnlp, hlt, ijcnlp, inlg, lre, lrec, ltc, mts, muc, naacl, paclic, ranlp, sem, tacl, tal, tain, tipster, trec | 40,751 |
| Speech-oriented | acltslp, csal, iccaspns, isca, jep, lre, lrec, ltc, mts, speechc, taslp | 53,264 |

Frontiers in Research Metrics and Analytics | www.frontiersin.org 3 July 2022 | Volume 7 | Article 863126
increased over time, as well as the number of completely new authors, who had never published at any previous conference or journal issue. The largest number of completely new authors was in 2020 (5,778 authors), comparable in a single year to the total number of different authors (5,688) who published over the 25 initial years (1965–1989)!

The percentage of new authors (Figure 6), which decreased from 100% in 1966 to 55% in 2011, increased since then to reach 65% in 2020, while the percentage of completely new authors, which decreased from 100% in 1966 to about 32% in 2011, now increased since then to reach 43% in 2020. This may reflect the arrival of "new blood" in the field, as it will be reflected in
the next sections related to the analysis of authors’ production, collaboration and citation, and the fact that researchers who started their careers in their 20s in 1965, which corresponds to the first year considered in our study, are now gradually retiring in their 70s.

If we compare sources, the percentage of completely new authors at the most recent event of conferences or journals within the past 5 years (Figure 7) ranges from 39% for TALN or 43% for the JEP to 87% for RANLP or 81% for EACL, while the largest conferences show relatively low percentages (48% for ISCA, 51% for IEEE ICASSP, 55% for ACL, and 56% for EMNLP). Compared with 2015, we notice a global increase in the percentage of completely new authors, especially in conferences and journals related to NLP.

We defined the author variety as the ratio of the number of different authors to the number of authorships4 at each conference. This ratio would be 100% if each author’s name appears in only one paper. Author redundancy corresponds to 100% author variety. Author redundancy increased over time and has now stabilized at about 40% since 2008 (Figure 8). Author redundancy is large in conferences such as ISCA or ICASSP, whereas it is lower in journals and slightly increased globally since 2015 (Figure 9).

Papers and Authorship
The number of authorships increases from 32 in 1965 to 22,610 in 2020 at even a higher pace than the number of papers (Figure 10).

Authors’ Gender
The author gender study is performed with the help of a lexicon of given names with gender information (male, female, epicene5). As already noted, variations due to different cultural habits for naming people (single vs. multiple given names, family vs. clan names, inclusion of honorific particles, ordering of the components, etc.) (Fu et al., 2010), changes in editorial practices,

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4“Authorship” is the signature of a paper by a given author, whatever the number of affiliations he/she may have. If an author published two papers in a conference, it counts for two authorships for this author.

5“Epicene” means that the given name is gender ambiguous.
FIGURE 6 | Percentage of new authors and completely new authors over time.

FIGURE 7 | Percentage of completely new authors in the most recent event across the sources in 2020 (red) and difference with 2015 (blue).

FIGURE 8 | Author redundancy over time.
FIGURE 9 | Author redundancy across the sources in 2020 (red) and difference with 2015 (blue).

FIGURE 10 | Number of papers and authorships over time.

FIGURE 11 | Gender of the authors’ contributions over time.
and sharing of the same name by large groups of individuals contribute to make identification by name a real issue (Vogel and Jurafsky, 2012). In some cases, we only have an initial for the first name, which made gender guessing impossible unless the same person appears with his/her first name in full in another publication. Although the result of the automatic processing was hand-checked by an expert of the domain for the most frequent names, the results presented here should therefore be considered with caution, allowing for an error margin.

A total of 46% of the authors are male, whereas 14% are female, 4% are epicene, and 36% are of unknown gender. Considering the paper authorships, which take into account the authors’ productivity, and assuming that the authors of unknown gender have the same gender distribution as the ones that are categorized, male authors account in 2020 for 80% (compared to 83% in 2015) and female authors for 20% (compared to 17% in 2015) of the authorships (Figure 11), hence a slight improvement.

IEEE TASLP and ICASSPS have, in 2020 just as in 2015, the most unbalanced situation (respectively, 10 and 13% of female authors), whereas the French conferences (JEP, TALN) and journals (TAL), together with LRE and LREC, have a better balanced one (from 30 to 41% of female authors). The largest increase over the past 5 years (+4%) appears for JEP and TACL (Figure 12).

### Authors’ Production and Co-production
The most productive author published 453 papers, whereas 36,791 authors (55% of the 66,995 authors) published only one paper. Table 3 gives the list of the 12 most productive authors. We see that the eight most productive authors are the same than in 2015, with a slightly different ranking. A total of two newcomers are ranked 9 and 10, specialized in machine learning (ML): James R. Glass (unsupervised ML) and Yang Liu (Federated ML). Some authors (James Glass, Yang Liu, Haizhou Li, Satoshi Nakamura, and Shri Narayanan) increased their number of papers by 30% and more within the past 5 years!
But if we focus on the past 5 years (2016–2020) (Table 4), we notice that only two authors (Shrikanth S. Narayanan and Haizhou Li) still appear in that ranking. Others energetically contributed to the research effort on speech and language processing with a new angle benefiting from supervised or unsupervised machine-learning approaches, some already active in that field but also many new names, showing the great vitality of a new generation of researchers, who published more than 15 papers per year in this recent 5-year period.

**Collaborations**

**Authors’ Collaborations**

The number of authors per paper still increases, with more than 4 authors per paper on average, compared with 3.5 in 2015 (Figure 13).

Table 5 gives the number of authors who published papers as single authors, and the names of the ones who published 10 papers or more. A total of 60,193 authors (90% of the authors) never published a paper as single author. The ranking is very similar to 2015, including six newcomers (Mark Huckvale, Mark Jan Nederhof, Hagai Aronowitz, Philip Rose, Shunichi Ishihara, and Oi Yee Kwong).

The number of papers with a single author decreased from 75% in 1965 to 3% in 2020, illustrating the changes in the way research that is being conducted.

Up to 2015, the paper with the largest number of co-authors was a META-Net paper published at LREC 2014 (44 co-authors). It is now surpassed by three other papers:

- A paper with 45 co-authors from Microsoft published in TACL 2020
- A paper with 47 co-authors on the European Language Technology landscape published at LREC 2020
- A paper with 47 co-authors on the Language Technology landscape published at LREC 2020

| #Papers | #Authors | Author name |
|---------|----------|-------------|
| 28      | 1        | W. Nick Campbell |
| 26      | 1        | Jerome R. Belegarda |
| 24      | 2        | Ellen M. Voorhees, Olivier Ferret |
| 21      | 1        | Ralph Grishman |
| 20      | 1        | Takayuki Arai |
| 18      | 2        | Mark A. Johnson, Rathinavelu Chengalvarayan |
| 17      | 3        | Beth M. Sundheim, Douglas B. Paul, Kenneth C. Littkowski |
| 16      | 3        | Jerry R. Hobbs, Oi Yee Kwong, Steven M. Kay |
| 15      | 1        | Donna Harman |
| 14      | 4        | Dominique Desbois, John Makhouli, Patrick Saint-Dozier, Sadakki Furui |
| 13      | 4        | Eckhard Bick, Paul S. Jacobs, Rens Bod, Robert C. Moore |
| 12      | 11       | David S. Palett, Harvey F. Silverman, Jen Tzung Chien, Jörg Tiedemann, Lynette Hirschman, Marius A. Pasca, Martin Kay, Reinhard Rapp, Stephen Tomlinson, Ted Pedersen, Yorick Wilks |
| 11      | 10       | Dekang Lin, Eduard H. Hovy, Hagai Aronowitz, Michael Schützen, Philip Rose, Philippe Blache, Roger K. Moore, Shunichi Ishihara, Stephanie Senet, Tomek Strzalkowski Aravind K. Joshi, Hermann Ney, Hugo Van Hamme, Joshua T. Goodman, Karen Spärck Jones, Kenneth Ward Church, Kulip K. Paliwal, Mark Hepple, Mark A. Huckvale, Mark Jan Nederhof, Olov Engwall |

We notice a small discrepancy in the numbers due to the 2015 papers which were not counted in the previous study.

Keynote papers are not taken into account if their content was not included in the conference proceedings.
• A paper with 58 co-authors on the I4U Speaker Recognition NIST evaluation 2016 published at Interspeech 2017.

The most collaborating author collaborated with 403 different co-authors, whereas 2,430 authors only published alone. An author collaborates on average with 7.9 other authors (compared to 6.6 in 2015), whereas 157 authors published with 100 or more different co-authors. Table 6 provides the list of the 12 authors with the highest number of co-authors.

Table 7 provides the list of the 12 authors who had the largest number of collaborations, possibly with the same co-authors. As we can see, some authors increased a lot, and even doubled, the number of co-authors and of collaborations in the recent years, whereas there are seven newcomers in the ranking (Björn

### Table 6 | The 12 authors with the largest number of co-authors (up to 2020, in comparison with 2015).

| Name                    | #Co-authors | Rank 2020 | Previous rank 2015 | Previous #co-authors | New #co-authors 2015–2020 |
|-------------------------|-------------|-----------|--------------------|-----------------------|---------------------------|
| Shrikanth S. Narayanan  | 403         | 1         | 1                  | 299                   | 104                       |
| Haizhou Li              | 355         | 2         | 3                  | 252                   | 103                       |
| Satoshi Nakamura        | 292         | 3         | 4                  | 234                   | 58                        |
| Björn W. Schuller       | 291         | 4         | 39                 | 135                   | 156                       |
| Yang Liu                | 290         | 5         | 12                 | 128                   | 111                       |
| Hermann Ney             | 288         | 6         | 2                  | 254                   | 34                        |
| Sanjeev Khudanpur       | 284         | 7         | 8                  | 193                   | 91                        |
| Khalid Choukri          | 253         | 8         | 15                 | 177                   | 76                        |
| Ming Zhou               | 246         | 9         | 7                  | 115                   | 131                       |
| Chin Hui P. Lee         | 241         | 10        | 7                  | 194                   | 47                        |
| Dong Yu                 | 241         | 10        | 187                | 82                    | 159                       |
| Alan W. Black           | 238         | 12        | 25                 | 149                   | 89                        |

### Table 7 | The 12 authors with the largest number of collaborations (up to 2020, in comparison with 2015).

| Name                    | #Collaborations 2020 | Previous #collaborations 2015 | New collaborations 2015–2020 |
|-------------------------|-----------------------|-------------------------------|-----------------------------|
| Shrikanth S. Narayanan  | 1,411                 | 1,035                         | 376                         |
| Haizhou Li              | 1,288                 | 899                           | 389                         |
| Hermann Ney             | 1,026                 | 890                           | 136                         |
| Satoshi Nakamura        | 983                   | 672                           | 189                         |
| Björn W. Schuller       | 841                   | 408                           | 433                         |
| Helen M. Meng           | 717                   | 337                           | 390                         |
| Dong Yu                 | 716                   | 293                           | 423                         |
| Chin Hui P. Lee         | 710                   | 544                           | 166                         |
| Junichi Yamagishi       | 685                   | 332                           | 353                         |
| Ming Zhou               | 680                   | 315                           | 365                         |
| Alex Waibel             | 679                   | 580                           | 99                          |
| Bin Ma                  | 670                   | 503                           | 167                         |

### Table 8 | The 12 authors with the largest number of co-authors in the past 5 years (2016–2020).

| Rank | Name                    | #Co-authors |
|------|-------------------------|-------------|
| 1    | Graham Neubig           | 193         |
| 1    | Björn W Schuller        | 193         |
| 3    | Yue Zhang               | 187         |
| 4    | Dong Yu                 | 175         |
| 4    | Yu Zhang                | 175         |
| 6    | Haizhou Li              | 161         |
| 7    | Kongak Lee              | 158         |
| 8    | Shrikanth S. Narayanan  | 154         |
| 9    | Ming Zhou               | 151         |
| 10   | Shinji Watanabe         | 145         |
| 10   | Jan Hajic               | 145         |
| 12   | Yang Liu                | 143         |

### Figure 14 | Mean degree of the collaboration graph for the 34 sources in 2015 (blue) and 2020 (red).
TABLE 9 | Computation and comparison of the closeness centrality, degree centrality, and betweenness centrality for the 10 most central authors (up to 2020, in comparison with 2015).

| Rank 2020 | Previous rank 2015 | Author’s name | Harmonic centrality | Norm on first | Rank 2020 | Previous rank 2015 | Author’s name | Degree centrality | Index and norm on first | Rank 2020 | Previous rank 2015 | Author’s name | Betweenness centrality | Index | Norm on first |
|-----------|---------------------|----------------|---------------------|--------------|-----------|---------------------|----------------|-------------------|---------------------|-----------|---------------------|----------------|------------------------|--------|--------------|
| 1         | 8                   | Sanjeev Khudanpur | 17863.281           | 1            | 1         | 1                   | Shrikanth S Narayanan | 1                | 1                  | Shrikanth S Narayanan | 44717979 | 1                   |
| 2         | 5                   | Haizhou Li       | 17782.575           | 0.995        | 2         | 3                   | Haizhou Li          | 0.881            | 2                  | Haizhou Li          | 34084103 | 0.762              |
| 3         | 2                   | Shrikanth S Narayanan | 17709.094          | 0.991        | 3         | 4                   | Satoshi Nakamura    | 0.725            | 3                  | Yang Liu           | 32048199 | 0.717              |
| 4         | 1                   | Mari Ostendorf   | 17565.169           | 0.983        | 4         | 41                  | Björn W Schuller    | 0.722            | 4                  | Satoshi Nakamura    | 28679912 | 0.641              |
| 5         | 3                   | Chin Hui P Lee   | 17454.696           | 0.977        | 5         | 12                  | Yang Liu            | 0.72             | 5                  | Chin Hui P Lee      | 25896571 | 0.579              |
| 6         | 6                   | Julia B Hirschberg | 17449.533          | 0.977        | 6         | 2                   | Hermann Ney         | 0.715            | 6                  | Laurent Besacier    | 25076596 | 0.561              |
| 7         | 15                  | Yang Liu         | 17442.071           | 0.976        | 7         | 8                   | Sanjeev Khudanpur   | 0.705            | 7                  | Alan W Black        | 23527696 | 0.526              |
| 8         | 11                  | Alan W Black     | 17409.874           | 0.975        | 8         | 15                  | Khalid Choukri      | 0.628            | 8                  | Khalid Choukri      | 22889904 | 0.512              |
| 9         | 4                   | Hermann Ney      | 17272.551           | 0.967        | 9         | 14                  | Ming Zhou           | 0.61             | 9                  | Sanjeev Khudanpur   | 21917631 | 0.49               |
| 10        | 115                 | Dong Yu          | 17249.284           | 0.966        | 10        | 7                   | Chin Hui P Lee      | 0.598            | 10                 | Hermann Ney         | 21262259 | 0.475              |
|           |                     |                 |                     |              |           |                     |                 |                  |                     |           |                     |                 |                        |        |              |
Schüller, Khalid Choukri, Dong Yu, Alan Black, Helen Meng, Junichi Yamagishi, and Ming Zhou).

If we focus on the past 5 years (2016–2020), we see that only three authors (Haizhou Li, Shri Narayanan, and Yang Liu) are still among the 12 authors with the largest number of co-authors (Table 8), whereas we notice many new names, often of Asian origin (Yue Zhang, Dong Yu, Yu Zhang, Kongaik Lee, Ming Zhou, and Shinji Watanabe) who constitute a new community around the use of supervised or unsupervised machine-learning approaches.

Collaboration Graph
The NLP4NLP+5 collaboration graph (refer to Appendix 4) contains 66,995 nodes corresponding to the 66,995 different authors (48,894 in 2015) and 163,189 edges between these nodes (162,497 in 2015).

When comparing the various sources, we do not notice any meaningful changes between 2015 and 2020 regarding the number of citations of NLP4NLP+5 papers. If we consider the papers that were published in joint conferences as different papers, the number of references is equal to 585,531. If we consider them as the same paper, the number of references in NLP4NLP+5 papers goes down to 535,989 and is equal to the number of citations of NLP4NLP+5 papers.

The average number of NLP4NLP+5 references in NLP4NLP+5 papers increased over time from close to 0 in 1965 to 12.7 in 2020 (was 9.7 in 2015) (Figure 14), as a result of the citing habits and of the increase in the number of published papers.

Measures of Centrality in the Collaboration Graph
As we see in Table 9, some authors in the top 10 in terms of closeness centrality also appear in the two other types of centralities (degree centrality and betweenness centrality), eventually with a different ranking, whereas others do not. Compared with 2015, we notice “newcomers” among the 10 most “central” authors:

- Yang Liu, Alan Black, Dong Yu (closeness centrality: those who are central in a community)
- Björn Schuller, Yang Liu, Khalid Choukri, Ming Zhou, Dong Yu (degree centrality: those who most collaborate)
- Laurent Besacier, Alan Black, Sanjeev Khudanpur (betweenness centrality: those who make bridges between communities).

If we consider the period 2016–2020, we see that only Sanjeev Khudanpur is still among the 10 most central authors, in terms of closeness centrality (Table 10).

In addition to that, only three authors among the 10 most “Betweenness Central” authors up to 2015 are still in the ranking for the 2016–2020 period (Shri Narayanan, Yang Liu, and Haizhou Li). New authors may bring bridges with new scientific communities. Some authors may be absent from this 2016–2020 ranking, while increasing their global “up to 2020” ranking in this period due to the enlargement of previous communities (Table 11).

Citations
Global Analysis
We studied citations of NLP4NLP+5 papers in the 78,927 NLP4NLP+5 papers that contain a list of references. If we consider the papers that were published in joint conferences as different papers, the number of references is equal to 585,531. If we consider them as the same paper, the number of references in NLP4NLP+5 papers goes down to 535,989 and is equal to the number of citations of NLP4NLP+5 papers.

The average number of NLP4NLP+5 references in NLP4NLP+5 papers increased over time from close to 0 in 1965 to 12.7 in 2020 (was 9.7 in 2015) (Figure 15), as a result of the citing habits and of the increase in the number of published papers.

The trend concerning the average number of citations per paper over the years (Figure 16) is less clear. Obviously, the most recent papers are less cited than the older ones, with a number of more than nine citations on average per paper for the papers of the most cited year (2003) and less than one citation on average for the papers published in 2020, given that they can only be cited by the papers published on the same year. It seems that papers need on average 3 years after publication to be properly cited, and that the average number of citations for a paper is
stabilized at about 6–8 citations per paper if we consider the period 1993–2018.

Among the 66,995 authors, 23,850 (36%) are never cited (even 25,281 (38%) if we exclude self-citations). These percentages slightly improved compared with 2015 (respectively, 42 and 44%). However, those never cited authors may come from neighboring research domains (artificial intelligence, machine learning, medical engineering, acoustics, phonetics, general linguistics, etc.), where they may be largely cited. Among the 85,138 papers, 31,603 (37%) are never cited [even 40,111 (47%) if we exclude self-citations by the authors of these papers] also showing a slight improvement compared with 2015 (respectively, 44 and 54%) (Table 12).

Analysis of Authors’ Citations
Most Cited Authors
Table 13 gives the list of the 20 most cited authors up to 2020, with the number of citations for each author, the number of papers written by the author, and the percentage of self-citation with a comparison to 2015. We may notice that the seven most cited authors up to 2015 are still present in 2020, but that 50% of the authors of 2020 (mostly attached to the machine learning and word embedding research-based communities) are newcomers in this ranking.

Table 14 provides the number of citations, either by themselves (self-citations) or by others (external citations), for the most productive authors that appear in Table 3. We see that only two of the 20 most productive authors (Herman Ney, Li Deng) also appear among the 20 most cited authors.

We may express that the publishing profile is very different among authors. The authors who publish a lot are not necessarily the ones who are the most cited (from 1.75 to 15 citations per paper on average) and the role of authors varies, from the main contributor to team manager, depending on their place in the authorship list and the cultural habits. Some authors are used to cite their own papers, while others are not (from 0.6 to 2.9 citations of their own paper on average).

If we now only consider the 2016–2020 period (papers published over 55 years that are cited in this 5-year period) (Table 15), we see that only one author of the 2015 ranking (Chris Manning) is still among the 20 most cited authors for this period!
Some authors who published a small number of seminal papers got a huge number of citations (such as Jeffrey Pennington, for the “Glove paper,” with two papers totaling 2,586 citations, with no self-citation!). However, as it will appear in the next section, getting a high h-index necessitates both publishing a lot and having a lot of citations of these published papers.

Authors’ H-Index

Despite the criticisms that are attached to this measure and as it was included in our previous paper, we computed the h-index of the authors based only on the papers published in the NLP4NLP+5 corpus. Table 16 provides the list of the 20 authors with the largest h-index up to 2020, with a comparison to 2015 (based on the papers published and cited in the respective 55- and 50-year time periods). We see that Christopher Manning has still the largest h-index:

TABLE 12 | Absence of citations of authors and papers within NLP4NLP+5.

| Number       | Percentage | Previous |
|--------------|------------|----------|
| Papers never referenced | 31,603 | 37 | 44 |
| Papers never referenced (aside self ref) | 40,111 | 47 | 54 |
| Authors never referenced | 23,850 | 36 | 42 |
| Authors never referenced (aside self ref) | 25s,281 | 38 | 44 |

TABLE 13 | A total of 20 most cited authors up to 2020.

| Rank 2020 | Previous rank 2015 | Name | #Citations | Nb of papers written by this author | Ratio #citations/nb of papers written by this author | Percentage of self-citations |
|-----------|---------------------|------|-------------|------------------------------------|-----------------------------------------------------|-----------------------------|
| 1         | 3                   | Christopher D. Manning | 13,195 | 152 | 86.809 | 2.145 |
| 2         | 1                   | Hermann Ney | 7,109 | 388 | 18.322 | 16.205 |
| 3         | >20                 | Christopher Dyer | 5,372 | 114 | 47.123 | 3.984 |
| 4         | >20                 | Richard Socher | 5,175 | 37 | 139.865 | 1.198 |
| 5         | 2                   | Franz Josef Och | 5,041 | 42 | 120.024 | 1.825 |
| 6         | 5                   | Dan Klein | 4,945 | 130 | 38.038 | 6.249 |
| 7         | 4                   | Philipp Koehn | 4,726 | 59 | 80.102 | 6.412 |
| 8         | >20                 | Noah A. Smith | 4,648 | 160 | 29.05 | 6.713 |
| 9         | 7                   | Andreas Stolcke | 4,532 | 145 | 31.255 | 6.355 |
| 10        | 6                   | Michael John Collins | 4,256 | 69 | 61.681 | 3.196 |
| 11        | >20                 | Kenton Lee | 4,251 | 21 | 202.429 | 0.729 |
| 12        | >20                 | Luke S. Zettlemoyer | 4,158 | 92 | 45.196 | 5.075 |
| 13        | 9                   | Salim Roukos | 4,132 | 71 | 58.197 | 1.5 |
| 14        | 18                  | Daniel Jurafsky | 4,056 | 118 | 34.373 | 2.342 |
| 15        | >20                 | Kristina Toutanova | 4,055 | 47 | 86.277 | 0.764 |
| 16        | >20                 | Sanjeev Khudanpur | 4,051 | 135 | 30.007 | 6.492 |
| 17        | >20                 | Daniel Povey | 3,796 | 112 | 33.893 | 7.929 |
| 18        | 16                  | Li Deng | 3,672 | 201 | 18.269 | 14.842 |
| 19        | >20                 | Dong Yu | 3,653 | 177 | 20.638 | 10.895 |
| 20        | >20                 | Mirella Lapata | 3,578 | 138 | 25.928 | 6.987 |

If we consider the h-index in the past 5 years (based on the papers published on 55 years and cited in the 2016–2020 period) (Table 17), we see that only five authors (Chris Manning, Noah Smith, Dan Klein, Daniel Jurafsky, and Mirella Lapata) with the highest h-index up to 2015 are still in the top 20 authors with the highest h-index for the 2016–2020 period!

Analysis of Papers’ Citations

Most Cited Papers

Table 18 provides the list of the 20 most cited papers up to 2020 and a comparison with 2015. A number of 11 (55%) of the 20 most cited papers up to 2015 are still among the 20 most cited papers up to 2020, whereas it includes five newcomers and four papers published in or after 2015, with a special emphasis on word embedding and deep learning (Glove and BERT). The most cited paper up to 2015 is still the most cited up to 2020 (BLEU MT evaluation measure). The most cited papers are still mostly those related to language data (Penn Treebank, Wordnet, and Europarl), evaluation metrics (BLEU), language processing tools (Glove, BERT, Moses, SRILM), or methodology surveys (word representations, statistical alignment, statistical and neuronal machine translation). The largest number of
### TABLE 14: The number of citations for the 20 most productive authors (1965–2020).

| Rank | Name                              | #writtenpapers | #as first author | % as first author | #as last author | % as last author | #sole author | % as sole author | Rank citations | #self-citations | Ratio of #self-citations/number of written papers | #external citations | Ratio of #external citations/number of written papers |
|------|-----------------------------------|----------------|------------------|-------------------|-----------------|-----------------|--------------|-----------------|----------------|----------------|-----------------------------------------------|-------------------|--------------------------------------------------|
| 453  | Shrikanth S. Narayanan            | 13             | 3                | 86                | 0               | 0               | >20          | 782             | 1.726          | 2,129          | 4.7                                           | 2,129             | 4.7                                             |
| 388  | Hermann Ney                       | 27             | 7                | 325               | 10              | 3               | 2            | 1,152           | 2.969          | 5,967          | 15.353                                        | 5,967             | 15.353                                           |
| 354  | John H. L. Hansen                 | 29             | 8                | 283               | 3               | 1               | >20          | 779             | 2.201          | 1,076          | 3.04                                          | 1,076             | 3.04                                            |
| 350  | Haizhou Li                        | 13             | 4                | 256               | 2               | 1               | >20          | 490             | 1.4            | 1,623          | 4.637                                        | 1,623             | 4.637                                           |
| 263  | Satoshi Nakamura                  | 17             | 6                | 190               | 1               | 0               | >20          | 160             | 0.608          | 648            | 2.464                                        | 648               | 2.464                                           |
| 261  | Chin Hui P. Lee                   | 14             | 5                | 207               | 5               | 2               | >20          | 577             | 2.211          | 2,852          | 10.927                                       | 2,852             | 10.927                                          |
| 234  | Alex Waibel                       | 13             | 6                | 199               | 2               | 1               | >20          | 262             | 1.12           | 2,048          | 8.752                                        | 2,048             | 8.752                                           |
| 230  | Mark J. F. Gales                  | 31             | 13               | 105               | 9               | 4               | >20          | 638             | 2.774          | 2,923          | 12.709                                       | 2,923             | 12.709                                          |
| 214  | James R. Glass                    | 11             | 5                | 152               | 1               | 0               | >20          | 428             | 2              | 2,084          | 9.738                                        | 2,084             | 9.738                                           |
| 209  | Yang Liu                          | 48             | 23               | 83                | 3               | 1               | >20          | 240             | 1.148          | 2,080          | 9.952                                        | 2,080             | 9.952                                           |
| 204  | Lin Shan Lee                      | 10             | 5                | 189               | 0               | 0               | >20          | 328             | 1.608          | 656            | 3.216                                        | 656               | 3.216                                           |
| 201  | Li Deng                           | 57             | 28               | 73                | 6               | 3               | 18           | 545             | 2.711          | 3,127          | 15.557                                       | 3,127             | 15.557                                          |
| 197  | Hervé Bourlard                    | 10             | 5                | 141               | 3               | 2               | >20          | 277             | 1.406          | 940            | 4.772                                        | 940               | 4.772                                           |
| 195  | Mari Ostendorf                    | 29             | 15               | 100               | 5               | 3               | >20          | 309             | 1.585          | 2,136          | 10.954                                       | 2,136             | 10.954                                          |
| 195  | Tatsuya Kawahara                  | 33             | 17               | 110               | 0               | 0               | >20          | 248             | 1.272          | 708            | 3.631                                        | 708               | 3.631                                           |
| 192  | Björn W. Schuller                 | 40             | 21               | 105               | 0               | 0               | >20          | 511             | 2.661          | 1,583          | 8.245                                        | 1,583             | 8.245                                           |
| 188  | Keikichi Hirose                   | 28             | 15               | 95                | 1               | 1               | >20          | 140             | 0.745          | 330            | 1.755                                        | 330               | 1.755                                           |
| 183  | Frank K. Soong                    | 9              | 5                | 78                | 0               | 0               | >20          | 208             | 1.137          | 1,240          | 6.776                                        | 1,240             | 6.776                                           |
| 182  | Kiyohiro Shikano                  | 1              | 1                | 142               | 0               | 0               | >20          | 276             | 1.516          | 1,161          | 6.379                                        | 1,161             | 6.379                                           |
| 180  | Timothy Baldwin                   | 21             | 12               | 115               | 4               | 2               | >20          | 216             | 1.2            | 1,160          | 6.444                                        | 1,160             | 6.444                                           |
highly cited papers comes from the ACL conference (4), NAACL (3), the *Computational Linguistics* journal (3), and the *IEEE TASLP* (3), whereas four papers now come from the EMNLP conference, which was previously absent from this ranking.

While if we only consider the 20 most cited papers in the period of 2016–2020 (papers published over 55 years that are cited in this 5-year period) (Table 19), 75% of those papers were not in the 2015 ranking!
### TABLE 18 | The number of 20 most cited papers up to 2020.

| Rank 2020 | Rank 2015 | Title                                                                 | Authors                                                                 | Source | Year | \#Citations 2020 | \#Citations 2015 |
|-----------|-----------|----------------------------------------------------------------------|------------------------------------------------------------------------|--------|------|------------------|------------------|
| 1         | 1         | BLEU: a Method for Automatic Evaluation of Machine Translation      | Kishore A. Papineni, Salim Roukos, Todd R. Ward, Wei Jing Zhu          | acl    | 2002 | 3,020            | 1,514            |
| 2         | >20       | Glove: Global Vectors for Word Representation                        | Jeffrey Pennington, Richard Socher, Christopher D. Manning            | emnlp  | 2014 | 2,590            |                  |
| 3         | 0         | BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding | Jacob Devlin, Ming Wei Chang, Kenton Lee, Kristina Toutanova          | naacl  | 2019 | 2,468            |                  |
| 4         | 2         | Building a Large Annotated Corpus of English: The Penn Treebank     | Mitchell P. Marcus, Beatrice Santorini, Mary Ann Marcinkiewicz       | cl     | 1993 | 1,610            | 1,145            |
| 5         | 3         | Moses: Open Source Toolkit for Statistical Machine Translation      | Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, Christopher Dyer, Ondrej Bojar, Alexandra Constantin, Evan Herbst | acl    | 2007 | 1,380            | 860              |
| 6         | 5         | SRILM - an extensible language modeling toolkit                     | Andreas Stolcke                                                      | isca   | 2002 | 1,319            | 831              |
| 7         | >20       | Front-End Factor Analysis for Speaker Verification                 | Najim Dehak, Patrick J. Kenny, Réda Dehak, Pierre Dumouchel, Pierre Ouellet | taslp  | 2011 | 1,170            |                  |
| 8         | 0         | Deep Contextualized Word Representations                            | Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, Luke S. Zettlemoyer | naacl  | 2018 | 1,166            |                  |
| 9         | 4         | A Systematic Comparison of Various Statistical Alignment Models     | Franz Josef Och, Hermann Ney                                         | cl     | 2003 | 1,079            | 855              |
| 10        | 6         | Statistical Phrase-Based Translation                                | Philipp Koehn, Franz Josef Och, Daniel Marcu                         | hlt, naacl | 2003 | 1,038            | 829              |
| 11        | 7         | The Mathematics of Statistical Machine Translation: Parameter Estimation | Peter E. Brown, Stephen A. Della Pietra, Vincent J. Della Pietra, Robert L. Mercer | cl     | 1993 | 978              | 820              |
| 12        | 0         | Effective Approaches to Attention-based Neural Machine Translation | Thang Luong, Hieu Pham, Christopher D. Manning                       | emnlp  | 2015 | 907              |                  |
| 13        | 8         | Minimum Error Rate Training in Statistical Machine Translation      | Franz Josef Och                                                      | acl    | 2003 | 879              | 726              |
| 14        | >20       | Convolutional Neural Networks for Sentence Classification           | Yoon Chul Kim                                                       | emnlp  | 2014 | 862              |                  |
| 15        | 0         | Neural Machine Translation of Rare Words with Subword Units         | Rico Sennrich, Barry Haddow, Alexandra Birch                       | acl    | 2016 | 836              |                  |
| 16        | >20       | Wordnet: A Lexical Database For English                            | George A. Miller                                                   | hlt    | 1992 | 814              |                  |
| 17        | >20       | Spoken Language Translation                                        | Hwee Tou Ng                                                        | emnlp  | 1997 | 774              |                  |
| 18        | 15        | Europarl: A Parallel Corpus for Statistical Machine Translation     | Philipp Koehn                                                      | mts    | 2005 | 760              | 472              |
| 19        | 10        | Suppression of acoustic noise in speech using spectral subtraction  | Steven F. Boll                                                     | taslp  | 1979 | 728              | 566              |
| 20        | 13        | Speech enhancement using a minimum-mean square error short-time spectral amplitude estimator | Yariv Ephraim, David Malah                                           | taslp  | 1984 | 708              | 488              |

**Analysis of Citations Among NLP4NLP Sources**

**Comparison of NLP vs. Speech Processing Sources**

When comparing the number of articles being cited in NLP vs. speech-oriented publications (Figure 17), we see that this number is increasing much more importantly in the NLP ones since 2001, providing that 2020 cannot be considered due to the previously expressed reason.

This is also reflected in the ratio of NLP vs. speech articles' citations (Figure 18), given that we only had NLP sources until 1975. We then had a ratio of about 60% of NLP papers being cited from 1975 to 1989, then a balanced ratio until 2001, and since then an increasing percentage of NLP papers which attained 75% in 2019.

**Comparison of Citations for Six Major Conferences and Journals**

The comparative study of the number of cumulative citations of previously published papers in six important conferences (ACL, COLING, EMNLP, ICASSPS, ISCA, and LREC) shows
### TABLE 19 | The number of 20 most cited papers for the past 5 years (2016–2020).

| Rank | Name and title | Corpus | Year | Authors | #Citations |
|------|----------------|--------|------|---------|------------|
| 1    | Glove: Global Vectors for Word Representation | emnlp  | 2014 | Jeffrey Pennington, Richard Socher, Christopher D. Manning | 2,486 |
| 2    | BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding | naacl | 2019 | Jacob Devlin, Ming Wei Chang, Kenton Lee, Kristina Toutanova | 2,468 |
| 3    | BLEU: a Method for Automatic Evaluation of Machine Translation | acl | 2002 | Kishore A. Papineni, Salim Roukos, Todd R. Ward, Wei Jing Zhu | 1,491 |
| 4    | Deep Contextualized Word Representations | naacl | 2018 | Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, Luke S. Zettlemoyer | 1,166 |
| 5    | Effective Approaches to Attention-based Neural Machine Translation | emnlp  | 2015 | Thang Luong, Hieu Pham, Christopher D. Manning | 907 |
| 6    | Neural Machine Translation of Rare Words with Subword Units | acl | 2016 | Rico Sennrich, Barry Haddow, Alexandra Birch | 836 |
| 7    | Convolutional Neural Networks for Sentence Classification | emnlp | 2014 | Yoon Chul Kim | 820 |
| 8    | Front-End Factor Analysis for Speaker Verification | tsalp | 2011 | Najim Dehak, Patrick J. Kenny, Rêda Dehak, Pierre Dumouchel, Pierre Ouellet | 738 |
| 9    | Enriching Word Vectors with Subword Information | tacl | 2017 | Piotr Bojanowski, Edouard Grave, Armand Joulin, Tomáš Mikolov | 687 |
| 10   | Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation | emnlp | 2014 | Kyunghyun Cho, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, Yoshua Bengio | 566 |
| 11   | SQuAD: 100,000+ Questions for Machine Comprehension of Text | emnlp | 2016 | Pranav Rajpurkar, Jian Justin Zhang, Konstantin Lopyrev, Percy Liang | 556 |
| 12   | Moses: Open Source Toolkit for Statistical Machine Translation | acl | 2007 | Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, Christopher Dyer, Ondrej Bojar, Alexandra Constantin, Evan Herbst | 505 |
| 13   | Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank | emnlp | 2013 | Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng, Christopher Potts | 488 |
| 14   | Librispeech: An ASR Corpus Based on Public Domain Audio Books | icassps | 2015 | Vassil Panayotov, Guoguo Chen, Daniel Povey, Sanjeev Khudanpur | 474 |
| 15   | Recurrent neural network-based language model | isca | 2010 | Tomáš Mikolov, Martin Karafiát, Lukás Burget, Jan Horza Černocky, Sanjeev Khudanpur | 472 |
| 16   | Wordnet: A Lexical Database for English | hlt | 1992 | George A. Miller | 456 |
| 17   | Get To The Point: Summarization with Pointer-Generator Networks | acl | 2017 | Abigail See, Peter J. Liu, Christopher D. Manning | 455 |
| 18   | Building a Large Annotated Corpus of English: The Penn Treebank | cl | 1993 | Mitchell P. Marcus, Beatrice Santorini, Mary Ann Marcinkiewicz | 447 |
| 19   | A large annotated corpus for learning natural language inference | emnlp | 2015 | Samuel R. Bowman, Gabor Angeli, Christopher Potts, Christopher D. Manning | 446 |
| 20   | Neural Architectures for Named Entity Recognition | naacl | 2016 | Guillaume Lample, Miquel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, Christopher Dyer | 432 |

(Figure 19) that the number of ISCA papers being cited grows at a high rate over time, in agreement with the ISCA Board policy which decided in 2005 to enlarge the number of pages from 6 to 7, providing that the allowed extra page should only consist of references. The same appears more recently for ACL. ICASSPS comes in the third position, whereas EMNLP recently showed an important increase. We then find a group of two with COLING and LREC.

Doing the same on six major journals (Computational Linguistics, Computer Speech and Language, Language Resources and Evaluation, Speech Communication, IEEE Transactions on Audio, Speech, and Language Processing, and Transactions of the ACL) shows (Figure 20) the importance of the reference to the IEEE Transactions, followed by Computational Linguistics. The Transactions of the ACL recently made a large increase.
We considered (refer to Appendix 4) the 85,138 papers and the 66,995 authors in NLP4NL+5 in the citation graph, which includes 587,000 references. When comparing the sources, it should be remembered that the time periods are different, as well as the frequency and number of events for conferences or journals.

**Authors’ Citation Graph.** When comparing the various sources, there are also no meaningful changes between 2015 and 2020 regarding the diameter, density, average clustering coefficient, and connected components of the Internal Authors Citations and Ingoing Global Authors Citations that were presented in our previous paper.

The mean degree of the Outgoing Global Authors Citations graph of the **citing** authors (i.e., average number of authors being cited by each author), measuring the average number of authors citations within a source, shows a large increase for most sources (**Figure 21**), following the general trend (refer to **Figure 15**), especially recently in the NLP sources (TACL, EMNLP, ACL, CL, NAACL, IJCNLP, and CONLL) with more than 40 authors being cited by each author on average.

The mean degree of the Ingoing Global Authors Citations graph of the authors **being cited** in each of the 34 sources...
FIGURE 19 | Number of references to papers of 6 major conferences over the years.

FIGURE 20 | Number of references to papers of 6 major journals over the years.

FIGURE 21 | Mean Degree of authors citing authors in general for the 34 sources in 2015 (blue) and 2020 (red).

(Figure 22) shows that authors who publish in Computational Linguistics are still the most cited, but are now closely followed by authors in TACL, with a tremendous increase, then ACL, NAACL, HLT, and EMNLP, with more than 60 citations of each author on average.

Papers' Citation Graph. There are no meaningful changes between 2015 and 2020 regarding the diameter, density, average clustering coefficient, and connected components of the Internal Papers Citations and Ingoing Global Papers Citations, when comparing the various sources.
The mean degree of the Outgoing Global Papers Citations graph of the citing papers (i.e., average number of references in each paper), measuring the average number of papers citations within a source, shows an increase for most sources (Figure 23), following the general trend (refer to Figure 15), especially the NLP sources (TACL, CL, EMNLP, ACL, NAACL, IJCNLP, CONLL, CSAL, and LRE) with more than 10 references in each paper on average.

Figure 24 provides the average number of papers being cited from each of the 34 sources. Papers published in Computational Linguistics are still the most cited (more than 25 times on average), but are now more closely followed by various NLP sources (TACL, CL, EMNLP, ACL, NAACL, IJCNLP, CONLL, CSAL, and LRE) with more than 10 citations of each paper on average.

Sources’ H-Index
Figure 25 provides the internal h-index (NLP4NLP papers being cited by papers of any NLP4NLP source) for the 34 sources. The largest h-index is obtained by ACL, where 109 papers are cited 109 times or more in the NLP4NLP+5 papers, followed by EMNLP, which increased considerably its h-index over the past 5 years from 55 in 2015 to 90 in 2020, TASLP (84), ICASSPS (77), and ISCA Interspeech (76).

Analysis of the Citation in NLP4NLP Papers of Sources From the Scientific Literature Outside NLP4NLP

Extraction of References
In the internal NLP4NLP citation analysis, references were extracted through a highly reliable checking of titles, as we possess the knowledge of the NLP4NLP paper titles. We cannot use the same approach if we want to explore the citation of articles that were published in other sources than the NLP4NLP ones, as we do not have a list of the titles of all those articles. We therefore used a different approach based on the use of the ParsCit software (Councill et al., 2008) to identify the sources within the reference sections of articles for a limited set of NLP4NLP articles. This new process is resulted in a list of raw variants of source naming, which necessitated a manual cleaning, as it contained a lot of noise, followed by normalization and categorization in four categories (Conferences, Workshops, Journals, and Books).

All the cleaned variants for a given source are kept, for instance, a short name compared to an extended name. We then...
FIGURE 24 | Mean Degree of papers being cited for the 34 sources in 2015 (blue) and 2020 (red).

FIGURE 25 | Internal h-index of the 34 sources in 2015 (blue) and 2020 (red).

FIGURE 26 | Total number of references (blue) and of NLP4NLP references (red) in NLP4NLP papers yearly.
implemented an algorithm to detect the source names within the reference sections for all NLP4NLP papers. The detection is technically conducted by means of an intermediate computation of a robust key made of uppercase letters and normalization of separators, as the aim is to compare names on the ground of significant characters and to ignore noise and insignificant
details. We then use these data to compare the citations in NLP4NLP articles of the articles published within and outside NLP4NLP sources.

Global Analysis
Starting from 32,918 entries, we conducted the manual cleaning and categorization process which resulted in 13,017 different variants of the sources, and, after normalization, in the identification of 3,311 different sources outside the 34 NLP4NLP ones, corresponding to conferences (1,304), workshops (669), journals (1,109), and books (229).

Figure 26 provides the evolution of the total number of references, which attains 121,619 references in 2020 for a cumulated total of 1,038,468 references over the years, and of NLP4NLP references, which attains 72,289 in 2020 for a cumulated total of 654,340 references (63% of the total number of references) with this new calculation based on source detection. These numbers clearly illustrate the representativity of the 34 NLP4NLP sources totaling close to 20,000 references on average per source, compared with about 110 references on average per source for the 3,311 non-NLP4NLP sources.

Figure 27 provides the percentage of NLP4NLP papers in the references. After a hectic period both due to the small quantity and low quality of data, mostly OCRized, until 1976, the ratio of NLP4NLP references stabilized at about 60% until 1994. It then rose up to 67% in 2009 and slowly decreased since then to attain 60% in 2020 with the appearance of new publications.

Figure 28 provides the average number of references per paper globally and specifically to NLP4NLP papers. We see that this number increases similarly to attain an average of 25 references per paper, as a result of the citing habits, the increase of the number of publications and of published papers in the literature and the generalization of electronic publishing, as already expressed in section Global Analysis (Figure 15), where only NLP4NLP papers were considered based on title identification.

Specific Analysis of Non-NLP4NLP Sources
Some new sources attract many papers, which resulted in many citations, showing a drastic change in the publications habits. Figure 29 provides the number of references in NLP4NLP+5 papers to arXiv preprints, with a huge increase in the recent years (from two references in 2010 to 498 in 2015 and 12,751 in 2020).

Also, the number of references related to the publications in artificial intelligence, neural networks, and machine learning, such as the conference on Artificial Intelligence of the Association for the Advancement of Artificial Intelligence (aaai), the International Joint Conference on Artificial Intelligence (ijcai), the International Conference on Machine Learning (icml), the International Conference on Learning Representations (iclr), the Neural Information Processing Systems conference (NeurIPS, formerly nips), or the Machine Learning and Machine Learning Research Journals, greatly increased in the recent years (Figure 30).

Google Scholar H-5 Index
As of July 2021, Google Scholar (Table 20) places as we do ACL first in the ranking of the “Computational Linguistics” conferences and journals category with an h5-index of 157 and an h5-median of 275 within the past 5 years, followed by EMNLP (132), NAACL (105), COLING (64), TACL (59), ELRA LREC (52), SEMEVAL (52), EACL (52), WMT (47), CONLL (43), CSL (34), SIGDIAL (34), Computational

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8NLP4NLP sources are slightly different here, as it is no more possible to differentiate papers specifically related to speech in the ICASSP conference.

9http://scholar.google.com/citations?view_op=top_venues&hl=en&vq=eng_computationallinguistics
## Table 20 | Ranking of 28 top sources according to Google Scholar h5-index over the past 5 years (2016–2020)*, in comparison with the previous ranking over 2011–2015.

| Rank 2020 | Previous Rank 2015 | Name | h-5 Index | h-5 Median | Previous h-5 Index | Previous h-5 Median |
|-----------|---------------------|------|-----------|------------|---------------------|---------------------|
| 1         | 1                   | Meeting of the Association for Computational Linguistics (ACL) | 157 | 275 | 65 | 99 |
| 2         | 2                   | Conference on Empirical Methods in Natural Language Processing (EMNLP) | 132 | 235 | 56 | 81 |
| 3         | 5                   | Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (HLT-NAACL) | 105 | 195 | 48 | 71 |
| 4         | 3                   | IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) | 96 | 143 | 54 | 73 |
| 5         | 6                   | Conference of the International Speech Communication Association (INTERSPEECH) | 89 | 150 | 39 | 70 |
| 6         | 8                   | International Conference on Computational Linguistics (COLING) | 64 | 103 | 38 | 59 |
| 7         | 4                   | IEEE/ACM Transactions on Audio, Speech, and Language Processing | 60 | 87 | 51 | 78 |
| 8         | 7                   | Transactions of the Association for Computational Linguistics (TACL) | 59 | 136 |       |         |
| 9         | 7                   | International Conference on Language Resources and Evaluation (LREC) | 53 | 81 | 38 | 64 |
| 10        | 15                  | International Workshop on Semantic Evaluation (Semeval) | 52 | 93 | 23 | 41 |
| 10        | 16                  | Conference of the European Chapter of the Association for Computational Linguistics (EACL) | 52 | 98 | 21 | 34 |
| 12        | 20                  | Workshop on Machine Translation (WMT) | 47 | 74 | 18 | 24 |
| 13        | 13                  | Conference on Computational Natural Language Learning (CoNLL) | 43 | 77 | 24 | 36 |
| 14        | 10                  | Computer Speech & Language (CSL) | 34 | 49 | 32 | 51 |
| 14        | 19                  | Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL) | 34 | 51 | 18 | 27 |
| 16        | 18                  | IEEE Workshop on Automatic Speech Recognition and Understanding (ASRU) | 33 | 52 |       |         |
| 16        | 18                  | IEEE Spoken Language Technology Workshop (SLT) | 33 | 58 | 18 | 28 |
| 18        | 12                  | Computational Linguistics (CL) | 30 | 48 | 31 | 40 |
| 18        | 17                  | International Joint Conference on Natural Language Processing (IJCNLP) | 30 | 48 | 20 | 27 |
| 20        | 11                  | Speech Communication | 28 | 49 | 32 | 49 |
| 21        | 20                  | Workshop on Representation Learning for NLP | 27 | 72 |       |         |
| 22        | 12                  | Biomedical Natural Language Processing | 26 | 37 |       |         |
| 23        | 12                  | Workshop on Innovative Use of NLP for Building Educational Applications | 25 | 34 |       |         |
| 24        | 14                  | Language Resources and Evaluation (LRE) | 24 | 36 | 23 | 42 |
| 24        | 24                  | Odyssey: The Speaker and Language Recognition Workshop | 24 | 45 |       |         |
| 24        | 14                  | International Conference on Natural Language Generation (INLG) | 24 | 35 |       |         |
| 27        | 11                  | Natural Language Engineering | 23 | 48 |       |         |
| 28        | 14                  | IEEE International Conference on Semantic Computing | 22 | 31 |       |         |

*According to Google Scholar, "h5-index is the h-index for articles published in the last 5 complete years. It is the largest number h such that h articles published in 2016–2020 have at least h citations each. h5-median for a publication is the median number of citations for the articles that make up its h5-index".

Linguistics (30), and IJCNLP (30). In the “Signal Processing” category, Google Scholar places IEEE ICASSP (96) first, then ISCA Interspeech (89), IEEE TASLP (60), LREC (53), CSL (34), SIGDIAL (34), and Speech Communication (28). This ranking covers the past 5 years and therefore reflects the recent trends compared with our own results, which concern a smaller number of sources but a longer time period.

Most conferences of the field considerably increased, and some (such as ACL, EMNLP, NAACL, ISCA Interspeech, Semeval, EACL) even more than doubled, their h-index over the past 5 years, whereas journals stayed at about the same level, apart from the Transactions of the ACL (TACL), which was launched in 2013 and did not appear in the previous ranking. arXiv is also not considered here.

### Topics

**Archive Analysis**

Here, our objectives are 2-fold: i) to compute the most frequent terms used in the domain, ii) to study their variation over time. Like the study of citations, our initial input is the textual content of the papers available in a digital format or that had been scanned. It contains a grand total of 380,828,636 words, mostly in English, over 55 years (1965–2020).
| Rank | Term                      | Variants of all sorts                                                                 | #Occurrences | Frequency  | #Existences | Presence  | Occurrences / existences | Previous Rank | Delta Ranking |
|------|---------------------------|---------------------------------------------------------------------------------------|--------------|------------|-------------|-----------|-------------------------|---------------|---------------|
| 1    | Dataset                   | Data-set, data-sets, datasets                                                        | 240,691      | 0.00758    | 24,288      | 0.28969   | 9.91                    | 11            | 10            |
| 2    | Annotation                | Annotations                                                                           | 187,175      | 0.00589    | 19,942      | 0.23786   | 9.39                    | 4             | 2             |
| 3    | SR                        | ASR, ASRs, Automatic Speech Recognition, Speech Recognition, automatic speech recognition | 179,579      | 0.00566    | 25,916      | 0.30911   | 6.93                    | 2             | −1            |
| 4    | LM                        | LMs, Language Model, Language Models, language model, language models               | 164,944      | 0.00519    | 19,139      | 0.22826   | 8.62                    | 3             | −1            |
| 5    | HMM                       | HMMs, Hidden Markov Model, Hidden Markov Models, hidden Markov model, hidden Markov models | 155,335      | 0.00489    | 17,131      | 0.20433   | 9.07                    | 1             | −4            |
| 6    | Embedding                 | Embeddings                                                                            | 145,844      | 0.00459    | 11,804      | 0.14079   | 12.36                   | 29            | 23            |
| 7    | Classifier                | Classifiers                                                                            | 143,885      | 0.00453    | 18,540      | 0.22114   | 7.76                    | 6             | −1            |
| 8    | POS                       | POSs, Part Of Speech, Part of Speech, Part-Of-Speech, Part-of-Speech, Part-of-Speech, Pos, part of speech, part-of-speech | 135,022      | 0.00425    | 18,946      | 0.22598   | 7.13                    | 5             | −3            |
| 9    | NP                        | NPs, noun phrase, noun phrases                                                        | 111,726      | 0.00352    | 12,139      | 0.14479   | 9.20                    | 7             | −2            |
| 10   | Parser                    | parsers                                                                               | 107,678      | 0.00339    | 12,071      | 0.14398   | 8.92                    | 8             | −2            |
| 11   | Neural network            | ANN, ANNs, Artificial Neural Network, Artificial Neural Networks, NN, NNs, Neural Network, Neural Networks, NeuralNet, NeuralNets, neural net, neural nets, neural networks | 97,039       | 0.00306    | 18,724      | 0.22333   | 5.18                    | 17            | 6             |
| 12   | Metric                    | Metrics                                                                               | 95,056       | 0.00299    | 20,451      | 0.24393   | 4.65                    | 18            | 6             |
| 13   | Segmentation              | Segmentations                                                                         | 94,886       | 0.00299    | 14,033      | 0.16738   | 6.76                    | 9             | −4            |
| 14   | SNR                       | SNRs, Signal Noise Ratio, Signal Noise Ratios, signal noise ratio, signal noise ratios | 90,820       | 0.00286    | 8,517       | 0.10159   | 10.66                   | 10            | −4            |
| 15   | MT                        | MTIs, Machine Translation, Machine Translations, machine translation, machine translations | 88,790       | 0.0028     | 13,603      | 0.16225   | 6.53                    | 15            | 0             |
| 16   | Parsing                   | Parsings                                                                              | 75,189       | 0.00237    | 12,551      | 0.1497    | 5.99                    | 13            | −3            |
| 17   | DNN                       | DNNs, Deep Neural Network, Deep Neural Networks, deep neural network, deep neural networks | 74,921       | 0.00236    | 5,740       | 0.06846   | 13.05                   | 63            | 46            |
| 18   | GMM                       | GMMs, Gaussian Mixture Model, Gaussian Mixture Models, Gaussian mixture model, Gaussian mixture models | 74,820       | 0.00236    | 8,203       | 0.09784   | 9.12                    | 14            | −4            |
| 19   | n-gram                    | n-gram, n-grams, ngrams                                                              | 73,159       | 0.0023    | 11,285      | 0.1346    | 6.48                    | 21            | 2             |
| 20   | Semantic                  | Semantic                                                                              | 70,186       | 0.00221    | 16,697      | 0.19915   | 4.20                    | 12            | −8            |
| 21   | Decoder                   | Decoders                                                                              | 69,385       | 0.00219    | 10,274      | 0.12254   | 6.75                    | 71            | 50            |
| 22   | WER                       | WERs, Wer, word error rate, word error rates                                         | 69,297       | 0.00218    | 8,547       | 0.10194   | 8.11                    | 20            | −2            |
| 23   | LSTM                      | LSTMs, Support Vector Machine, Support Vector Machines, support vector machine, support vector machines | 68,445       | 0.00216    | 7,090       | 0.08457   | 9.65                    | 145           | 122           |
| 24   | SVM                       | SVMs, Support Vector Machine, Support Vector Machines                                 | 67,610       | 0.00213    | 9,005       | 0.10741   | 7.51                    | 19            | −5            |
| 25   | Iteration                 | Iterations                                                                            | 65,686       | 0.00207    | 15,372      | 0.18335   | 4.27                    | 16            | −9            |
As depicted in Mariani et al. (2019b), we distinguished SNLP-specific technical terms from common general English ones after syntactic parsing, with the hypothesis that when a sequence of words is inside the NLP4NLP+5 corpus and not inside the general language profile, the term is specific to the field of SNLP. The 88,752 documents reduce to 81,634 documents when considering only the papers written in English. They include 4,488,521 different terms (unigrams, bigrams, and trigrams) and 34,828,279 term occurrences. The 500 most frequent terms (including their
FIGURE 33 | Evolution of the terms “HMM” (in green) and “Neural Network” (in blue) over the past 30 years (1990 to 2020) according to their presence in the papers.

FIGURE 34 | Evolution of the terms “LSTM” (brown), “RNN” (green), “DNN” (blue) and “CNN” (red) over the past 5 years (from the 100th rank in 2015 to the 30th in 2020), according to their presence.

FIGURE 35 | Evolution of the terms “embedding” (red), “encoder” (green), “BERT” (brown), and “transformer” (blue) over the past 5 years (from the 100th rank in 2015 to the 40th in 2020), according to their presence.
synonyms and variations in upper/lower case, singular/plural number, US/UK difference, abbreviation/expanded form, and the absence/presence of a semantically neutral adjective) in the field of SNLP were computed over the period of 55 years.

We called “existence” the fact that a term exists in a document and “presence” the percentage of documents where the term exists. We computed in that way the occurrences, frequencies, existences, and presences of the terms globally and over time (1965–2020) and also the average number of occurrences of the terms in the documents where they appear (Table 21).

The ranking of the terms may slightly differ according to their frequency or to their presence. The most frequent term overall is “dataset,” which accounts for 7.6% of the terms and is present in 29% of the papers, whereas the most present term is “Speech Recognition,” which is present in 31% of the papers while accounting for 5.7% of the terms. The average number of occurrences of the terms in the documents where they appear varies a lot (from 4.2 for “semantic” to more than 13 for “Deep Neural Network” or 12 for “Embedding”).

We also compared the ranking with the 2015 one. A total of 17 of the 20 most frequent terms up to 2015 are still present in this list, with few changes. We see a large progress in the terms associated with the neural network and machine-learning approaches [“dataset,” “embedding,” “neural network,” “DNN (Deep Neural Networks),” “decoder,” and “LSTM (Long Short-Term Memory)’] and a small decrease for the terms related to previous approaches [“HMM (Hidden Markov Models),” “GMM (Gaussian Mixture Models),” “SVM (Support Vector Machine).”]

**Change in Topics**

The GapChart visualization tool that we developed (Perin et al., 2016) allows us to study the evolution of the terms over the years, based on their frequency or their presence. Figure 31 provides a glimpse of the evolution of topics over time, and we invite the reader to freely access the tool to get a better insight on the evolution of specific terms, such as those illustrated in the following figures.

Figure 32 provides the evolution of the 25 most present terms in the past 10-year period (2010–2020). We see that some terms stay in this list over 10 years, such as “dataset,” “metric,” or “annotation,” while terms related to neural network and machine-learning approaches (such as “embedding,” “encoder,” “BERT (Bidirectional Encoder Representations from Transformers),” “transformer,” “softmax,” “hyperparameter,” “epoch,” “CNN (Convolutional Neural Networks),” “RNN (Recurrent Neural Networks),” “LSTM,” and “DNN”) made a large progression.

We may also select specific terms. Figure 33 focuses on the terms “HMM” and “Neural Network” in the 30-year period (1990–2020). It shows the slight preference for “Neural Network” up to 1992, then the supremacy of “HMM” up to 2015 and the recent burst of “Neural Networks” starting in 2013.

The progress on terms related to neural networks and machine learning was especially spectacular over the past 5 years (2015–2020) (Figures 34–36).

**Tag Clouds for Frequent Terms**

Tag Clouds provide an estimate of the main terms used on a given year. For this purpose, we use TagCrowd to generate Tag Clouds. We conducted experiments on full texts and on papers’ abstracts and found that papers’ abstracts provide a more meaningful analysis as they are more synthetic and contain a larger ratio of technical terms compared with general language. Figures 37A,B provide the Tag Clouds for 2015 and 2020. We clearly see the burst of terms related to machine learning (“BERT,” “CNN,” “decoder,” “embedding,” “encoder,” “pretraining,” “transformer”) that were absent in 2015, and the sustainability of “neural network,” “annotation,” “metric,” and “LM (“Language Model”).

**Research Topic Prediction**

**Machine Learning for Time Series Prediction**

We explored the feasibility of predicting the research topics for the coming years based on the past (Francopoulo et al., 2016a).
We selected in the time series plug-in of the Weka\(^{14}\) machine-learning software package (Witten et al., 2011) the Gaussian Processes algorithm with an 18-year window that provided the best results on predicting the term frequency. We then applied this software to the full set of the NLP4NLP+5 corpus, year by year.

Table 22 provides the ranking of the most frequent terms in 2018 and 2019 with their observed frequency, the topic predicted...
by the selected Weka algorithm for 2020 based on the smallest gap between predictions and observations on the past rankings and the ranking actually observed in 2020. We see that the prediction to have the term within the most frequent top 10 is correct for 8 of them.

**Prediction Reliability**

As we published such predictions for the years 2016–2020 in our previous paper, we were eager to verify whether these predictions were correct or not. We thus compared these predictions with the actual figures for these 5 years (Table 23). It appears that the predictions were quite reliable: the number of terms correctly predicted to appear within the 10 top terms varies from 7 to 8 in the first 3 years (2016, 2017, and 2018) that follow the year when the prediction was made (2015) and then decreases to 4 on the 4th year (given that BERT did not exist at the time of the prediction and therefore could not be predicted) and 3 in the 5th year, whereas one term ("dataset") was correctly predicted with the right ranking for the 5 years. It therefore confirms the assumption we made in our previous papers that predictions seem to be reasonable within a 3-year horizon (unless a major discovery happens in the meanwhile) in this research domain.

**Scientific Paradigms Ruptures**

As expressed in our previous paper (Mariani et al., 2019b), “the difference between the prediction and the observation on each year provides a measure of the ‘surprise’ between what was expected and what actually occurred. The years where this ‘surprise’ is the largest may correspond to epistemological ruptures.” Figure 38 provides the evolution of this distance between 2011 and 2020, computed as the average absolute value of the difference between prediction and observation for the 200 most frequent terms. It suggests that 2012 was a year of big changes, which then reduced for 2 consecutive years and then slightly evolved since 2014.

The same distance between prediction and observation for a specific topic illustrates the way this term evolved compared with what was expected. Figure 39 shows the evolution of the “Deep Neural Network” (DNN) term. It suggests that the popularity (as measured by the frequency of the term) of this approach in the next year was underestimated up to 2015, then overestimated until 2018.

**Predictions for the Next 5 Years**

The predictions for the next 5 years (2021–2025) are provided in Table 24: it is expected that methods based on machine learning, word embedding, and neural networks will keep on attracting the researchers’ attention, with a sustained interest for “Language Models (LM)” and a growing interest for “BERT” and “transformer.”

![Figure 38](image1.png)

**FIGURE 38 |** Evolution of the distance between prediction and observation over the years.

![Figure 39](image2.png)

**FIGURE 39 |** Measure of the expectation of an emerging research topic: Deep Neural Networks (DNN).

| TABLE 24 | Predictions for the next 5 years (2021–2025). |
|---|---|
| Rank | Observed 2019 | Observed 2020 | Prediction 2021 | Prediction 2022 | Prediction 2023 | Prediction 2024 | Prediction 2025 |
| 1 | Dataset | Dataset | Dataset | Dataset | Dataset | Dataset | Dataset |
| 2 | Embedding | Embedding | Embedding | Embedding | BERT | BERT | BERT |
| 3 | Encoder | BERT | BERT | BERT | Embedding | Embedding | Embedding |
| 4 | LSTM | Annotation | Annotation | Annotation | Encoder | Encoder | Encoder |
| 5 | Decoder | Encoder | Encoder | Transformer | Transformer | Transformer | Transformer |
| 6 | LM | LM | LM | transformer | LM | Encoder | LM |
| 7 | Metric | Transformer | Annotation | LM | Annotation | LM | Annotation |
| 8 | BERT | SR | Metric | Metric | Metric | Metric | Metric |
| 9 | SR | Metric | SR | SR | SR | SR | SR |
| 10 | Annotation | LSTM | Decoder | Decoder | Decoder | Annotator | Decoder |

Predictions are marked in green.
## TABLE 25 | The number of 10 most present terms in 2020, with variants, date, authors, and publications where they were first introduced, number of occurrences and existences in 2020, number of occurrences, frequency, number of existences and presence in the 55-year archive, with ranking and average number of occurrences of the terms in the documents where they appear, and comparison with the ranking in 2015 (the terms which joined the top 10 are marked in green, while the 5 which went out are marked in orange with their new and former ranking).

| Rank 2020 | Previous Rank 2015 | Term | Variants of all sorts | Event when the term appeared | Authors who introduced the term | Documents | Archive #occurrences | Archive frequency | Archive #existence | Archive presence | Archive rank occurrences | Archive rank existences | Archive rank occurrence/existence ratio | #occurrences of the term in 2020 | #Existences in 2020 | Frequency in 2020 | Presence in 2020 |
|-----------|--------------------|------|-----------------------|-------------------------------|--------------------------------|-----------|---------------------|-------------------|-------------------|-----------------|--------------------------|--------------------------|-------------------------------|-----------------------------|---------------------|------------------------|------------------------|
| 1         | 1                  | Dataset | Data-set, data-sets, datasets | 1966 | Laurence Urdang | cath1966-3 | 240,691 | 0.0076 | 24,288 | 0.290 | 1 | 2 | 9.91 | 59,794 | 4,313 | 0.0224 | 0.795 |
| 2         | 30                 | Embedding | Embeddings | 1967 | Aravind K. Joshi, Danuta Hiz, Jane J. Robinson, Steven I. Laszlo | C67-1007 | 145,845 | 0.0046 | 11,804 | 0.141 | 6 | 25 | 12.36 | 37,346 | 3,193 | 0.0140 | 0.588 |
| 3         | 2                  | Metric | Metrics | 1965 | A Andreyewsky | C65-1002 | 95,056 | 0.0030 | 20,451 | 0.244 | 12 | 4 | 4.65 | 14,352 | 2,915 | 0.0054 | 0.537 |
| 4         | 7                  | Neural network | ANN, ANNs, Artificial Neural Network, Artificial Neural Networks, NN, NNs, Neural Network, Neural Networks, NeuralNet, NeuralNets, neural net, neural nets, neural networks | 1972 | P J. Brown | cath1972-21 | 97,031 | 0.0031 | 18,716 | 0.223 | 11 | 8 | 5.18 | 9,190 | 2,623 | 0.0034 | 0.483 |
| 5         | >200Encoder | Encoder | Encoders | 1968 | Raymond F. Erickson | cath1968-2 | 62,324 | 0.0020 | 6,874 | 0.082 | 28 | 74 | 9.07 | 21,444 | 2,350 | 0.0080 | 0.433 |
| 6         | 6                  | Annotation | Annotations | 1967 | Kenneth Janda, Martin Kay | cath1967-12 | 187,175 | 0.0059 | 19,942 | 0.238 | 2 | 5 | 9.39 | 21,751 | 2,160 | 0.0081 | 0.398 |
| 7         | 67                 | Hyperparameter | hyperparam, hyperparameters | 1989 | G Demoment | taslp1989-131 | 22,593 | 0.0007 | 7,900 | 0.094 | 104 | 58 | 2.86 | 5,232 | 2,110 | 0.0020 | 0.389 |
| 8         | 9                  | LM | LMs, Language Model, Language Models, language model, language models | 1965 | Sheldon Klein | C65-1014 | 164,564 | 0.0052 | 19,080 | 0.228 | 4 | 6 | 8.62 | 14,850 | 1,977 | 0.0056 | 0.364 |
| 9         | 14                 | NLP | Natural Language Processing | 1965 | Denis M. Manelski, Gilbert K. Krulke | C65-1018 | 46,094 | 0.0015 | 14,243 | 0.170 | 40 | 14 | 3.24 | 6,978 | 1,948 | 0.0028 | 0.359 |
| 10        | 146                | LSTM | | 1999 | Felix A. Gers, Fred Cummins, Juergen Schmidhuber | e99_93 | 68,445 | 0.0022 | 7,090 | 0.085 | 23 | 70 | 9.65 | 13,767 | 1,934 | 0.0051 | 0.356 |
### TABLE 25 | Continued

| Rank 2020 | Previous Rank 2015 | Term | Variants of all sorts | Event when the term appeared | Authors who introduced the term | Documents | Archive occurrences | Archive frequency | Archive existence | Archive rank occurrences | Archive rank existences | Archive rank occurrence/existence ratio | #Occurrences of the term in 2020 (by other people than the inventors) | #Existences in 2020 (by other people than the inventors) | Frequency in 2020 | Presence in 2020 |
|-----------|-------------------|------|-----------------------|-------------------------------|---------------------------------|-----------|-------------------|-------------------|-------------------|------------------------|------------------------|-------------------------------|-------------------------------------------|--------------------------------------|----------------|----------------|
| 12        | 3                 | Subset | Sub set, sub sets, sub-set, sub-sets, subsets | 1965                          | Denis M. Manelski, E. D. Pendergraft, Gilbert K. Kruee, Itiroo Sakai, N. Dale, C65-1025 Wojciech Skalmowski | C65-1006 C65-1018 C65-1021 | 65,243          | 0.0021            | 24,171            | 0.288                  | 26                     | 29                     | 2.70                        | 5,239                         | 1,913                       | 0.0020 | 0.353 |
| 14        | 6                 | Classifier | Classifiers | 1967                          | Aravind K. Joshi, Danuta Hiz | C67-1007 | 143,885          | 0.0045            | 18,540            | 0.221                  | 7                      | 13                     | 7.76                        | 11,125                         | 1,847                       | 0.0042 | 0.340 |
| 24        | 5                 | SR | ASR, ASRs, Automatic Speech Recognition, Speech Recognition, automatic speech recognition, speech recognition | 1965                          | Denis M. Manelski, Daniel Varga, Gilbert Kruee, Makoto Nagao, Toshiyuki Sakai | C65-1018 C65-1022 C65-1029 | 179,579          | 0.0056            | 25,916            | 0.309                  | 3                      | 1                      | 6.93                        | 14,630                         | 1,423                       | 0.0055 | 0.262 |
| 27        | 10                | Optimization | Optimization, optimisations, optimizations | 1967                          | Ellis B. Page | C67-1032 | 48,412           | 0.0015            | 15,221            | 0.182                  | 36                     | 13                     | 3.18                        | 3,514                          | 1,356                       | 0.0013 | 0.250 |
| 33        | 8                 | POS | POSs, Part Of Speech, Part of Speech, Part-Of-Speech, Parts Of Speech, Parts of Speech, Pos, part of speech, part-of-speech, parts of speech, parts-of-speech | 1965                          | Denis M. Manelski, Daniel Varga, Gilbert Kruee, Makoto Nagao, Toshiyuki Sakai | C65-1018 C65-1022 C65-1029 | 135,022          | 0.0042            | 18,946            | 0.226                  | 8                      | 14                     | 7.13                        | 7,278                          | 1,158                       | 0.0027 | 0.213 |
Innovation
New Terms Introduced by the Authors
We studied who introduced new terms which became popular, where and when, to assess the innovative contributions of authors and sources to the advances of the scientific domain (Mariani et al., 2018b). We considered the 81,634 documents written in English and the 61,431 authors who used the 4,488,498 terms contained in these documents. A number of 2,968 of these terms are present in the 22 documents of the first year (1965) that we considered as the starting date for the introduction of new terms, while we found 594,807 of these terms in the 5,313 documents published in 2020. We should stress that the birth of a term is only searched in the 34 NLP4NLP+5 sources and that it may have had a different meaning when it was first introduced.

Table 25 provides the ranked list of the 10 most popular terms according to their presence in 2020 and a comparison with the ranking in 2015. We should notice that 50% of the top 10 terms have changed, with a spectacular increase in the terms related to machine learning and neural networks (“embedding,” “encoder,” “hyperparameter,” and “LSTM”).

Measuring the Importance of Topics
In our previous paper, we proposed to measure the “innovation score” of a term, as the sum of the yearly presence of the term since its introduction.

Table 26 | Global ranking of the innovation score of the terms overall and specifically for speech and NLP up to 2020.

| Rank | Overall | NLP | Speech |
|------|---------|-----|--------|
| 1    | Speech recognition | Semantic | Speech recognition |
| 2    | Subset | NP | Spectral |
| 3    | Semantic | Syntactic | HMM |
| 4    | LM | POS | Filtering |
| 5    | Filtering | Parsing | Subset |
| 6    | POS | Subset | Acoustics |
| 7    | HMM | Parser | Gaussian |
| 8    | Iteration | Lexical | Fourier |
| 9    | Spectral | Machine translation | Acoustic |
| 10   | Metric | Annotation | Linear |

We initially considered the 1,000 most frequent terms over the 55-year period, but given the poor quality and low number of different sources and papers in the first years, we decided to only consider the 45-year period from 1975 to 2020. Table 26 provides the overall ranking of the terms overall and specifically for the NLP and speech processing categories. This list is very similar to the one we computed in 2015 with a slightly different ranking.

We studied the evolution of the cumulative presence of the terms over the years (percentage of papers containing a given term up to a given year), to check the changes in paradigm while avoiding the noise due to the conference frequency. Figure 40 provides the evolution of the 10 most popular terms according to this measure. Their global ranking over the years corresponds to the order of the terms in the legend of the figure, as it will be the case for all figures in this section Innovation. Percentages are provided either in relation to the total number of papers (qualified as “all papers”), or with the papers related to a specific topic (qualified as “topical papers”).

We see for example that Speech Recognition (“SR”) has been a very popular topic over the years, reaching a presence in close to 35% of the papers published up to 2008, then slightly decreasing.

Measuring Authors’ Innovation
We computed in a similar way an innovation score for each author, illustrating his or her contribution in the introduction and early use of new terms that subsequently became popular, as the sum over the years of the annual presence of the terms in papers published by the author (percentage of papers containing the term and signed by the author on a given year), overall and specifically for the NLP and for the speech processing categories (Table 27). The names in this table are also very similar to those of 2015, with a slightly different ranking.

This measure does not place on the forefront uniquely the “inventors” of a new topic, as it is difficult to identify them, given that we only consider a subset of the scientific literature (the NLP4NLP+5 corpus), but it includes the early adopters who published a lot when or just after the topic was initially introduced. Therefore, authors of highly cited papers introducing innovative approaches (such as GloVe or BERT recently) do not
fully benefit for their innovation, as many authors immediately adopted, used, and published with these approaches on the same year.

Measuring the Innovation in Sources
We also computed an innovation score for each source as the sum over the years of the annual presence of the terms in papers published in the source, conference or journal (percentage of papers containing the term which were published in the publication on a given year), overall and specifically for NLP and for Speech Processing (Table 28). The names in this table are also very similar to those of 2015, with a slightly different ranking (progress for EMNLP in NLP and ISCA overall and in Speech Processing).

Measuring the Contribution of Authors and Sources to a Specific Topic
We may also study the contributions of authors or sources to a specific topic, using the cumulative innovation score of authors and sources attached to this topic.

Contributions to the Study of “HMM”
Figure 41 provides the cumulative percentage of papers containing the term “HMM” published up to a given year by the 10 most contributing authors, ranked according to the innovation measure up to 2020\(^\text{15}\). Compared with 2015, we only observe the appearance of Junishi Yamagishi on innovative HMM-based speech synthesis.

We also do not observe much difference regarding the contributions of the various sources to HMMs (Figure 42), with the IEEE TASLP as a pioneer in this area since 1982\(^\text{16}\), while ISCA Conference series represents 45% and IEEE-ICASSP 25% of the papers published on HMM up to 2020 and publications that are placed in both speech and NLP (CSL, HLT, LREC) help to spread the approach from speech processing to NLP as well (ACL, EMNLP).

Contributions to the Study of “DNN”
We studied the authors’ contributions over the years\(^\text{17}\) to deep neural networks (“DNNs”) that recently gained a large audience, in terms of percentage of authors and papers (“presence”) mentioning the term (Figure 43).

We notice the important contribution of Asian authors to this topic (Figure 44), with the pioneering contributions of Dong Yu who published about 30% of the papers published on this topic until 2012. Compared with 2015, we notice larger changes than in the case of HMMs, as it is a more changing field, with the appearance of new names (Shinji Watanabe, Tomohiro Nakatani, Helen Meng, and Shri Narayanan).

We may then also study how an author contribution to a specific topic compares with his/her main contributions to other topics, and how it evolved over the years. Figure 45 illustrates the fact that the contributions of Dong Yu are essentially focused on deep neural networks and second on the Softmax function in the years 2011–2013.

Looking at the source contribution to “DNN,” we see that it started from the speech community (ISCA Interspeech and IEEE TASLP) and then diffused in the natural language processing community (starting with ACL) (Figure 46).

Contributions to the Study of “Embedding”
Similarly, we studied the authors’ contributions over the years\(^\text{18}\) to “Embedding” which was used for many years from the 70s but gained since 2015 a large audience, in terms of percentage of authors and papers (“presence”) mentioning the term (Figure 47).

Figure 48 shows the contribution of authors to the topic of Embedding, which both shows the individual contributions and

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\(^\text{15}\)Some authors have published earlier on that topic, but don’t belong to the 10 most contributive ones on the long run.

\(^\text{16}\)We only had access to IEEE ICASSP proceedings since 1990, while Computer Speech and Language started in 1986 and the ISCA Conference Series in 1987.

\(^\text{17}\)The term “DNN” appeared first in a paper published in 1990 (Yamaguchi et al., 1989), but with the meaning of “Dynamic Programming Neural Network”, with a reference to a paper published by Sakoe at ICASSP 1989 (which is not considered in NLP4NLP+5). However, the low presence of the term with this meaning rightly prevents these authors to appear among the main contributors to “DNN” in its present meaning.

\(^\text{18}\)Here also, the term appeared early in 1967, but with a different meaning and a low presence until the recent years.
the large increase in the presence of the topic since 2015, as illustrated in Figure 47.

In this case, the topic was initiated in the natural language processing community (COLING, ACL, IJCNLP) and then diffused in the speech community as well (ISCA Interspeech, ICASSP, TASLP) (Figure 49).

We may then also study how a source contribution to a specific topic compares with its main contributions to other topics, and how it evolved over the years. Figure 50 clearly illustrates the major contribution in the recent years of the EMNLP conference to the research on “embedding,” where almost 20% of the papers produced so far on this topic have been published.
FIGURE 44 | Cumulative authors’ contributions to the study of DNN in speech and NLP (% of topical papers).

FIGURE 45 | Main contribution areas for Dong Yu (% of topical papers).

FIGURE 46 | Cumulative sources’ contributions to “DNN” in speech processing and NLP (% of topical papers).
FIGURE 47 | Percentages of authors (blue) and of papers (red) mentioning “Embedding” in speech and NLP (% of all papers).

FIGURE 48 | Cumulative authors’ contributions to the study of “Embedding” in speech and NLP (% of topical papers).

FIGURE 49 | Cumulative sources’ contributions to the study of “Embedding” in speech and NLP (% of topical papers).
Use of Language Resources

The LRE Map

We have conducted an analysis of language resources (LR) as bricks that are used by the researchers to conduct their research investigations and develop their systems (Francopoulo et al., 2016b). We consider here language resources in the broad sense, embracing data (e.g., corpus, lexicons, dictionaries, terminological databases, language models, etc.), tools (e.g., morpho-syntactic taggers, prosodic analyzers, annotation tools, algorithms, software packages, etc.), system evaluation resources (e.g., metrics, training, dry run or test corpus, evaluation packages, etc.), and meta-resources (e.g., best practices, guidelines, norms, standards, etc.) that are mentioned in the LRE Map (Calzolari et al., 2012). This database is produced by the authors of papers at various conferences and workshops of the domain who are invited when submitting their paper to fill in a questionnaire which provides the main characteristics of the language resources produced or used in the research investigations that they report in their paper.

The version of the LRE Map that we used in our previous paper contained information harvested from the authors in 10 conferences from 2010 to 2012, for a total of 4,396 different resources. In the present paper, we use an updated version of the LRE Map containing data harvested in 53 conferences and workshops from 2010 to 2018 (6 more years), for a total of 9,725 resources, that we cleaned up (correct the name of the resources, eliminate the duplicates, regroup the various versions of resources from the same family, etc.). We finally ended up with 5,609 different resources that we searched in the articles of the NLP4NLP+5 corpus.

Evolution of the Use of Language Resources

Figure 51 provides the evolution of the number of different resources mentioned in the papers (that we call “existence”) compared with the evolution of the number of papers over the years, whereas Figure 52 provides the average number of language resources mentioned in a paper (that we call “presence”). The corresponding curves cross in 2002, when more than one language resource was mentioned on average in a paper, reflecting the shift from knowledge-based approaches to data-driven approaches in SNLP research. Since 2015, the number of mentions of language resources largely increased, to attain 16,000 mentions in 2020, whereas the number of papers also greatly increased, and the ratio stays at about 3 language resources mentioned in a paper on average.

Table 29 provides the ranking of language resources according to their “existence” (number of papers where they are mentioned), their type (corpus, lexicon, tool, etc.), their number of “occurrences” (number of mentions in the papers), the first authors who mentioned them as well as the first publications, and the first and final years when they were mentioned, and a comparison with the 2015 ranking. We see that half of the language resources that were in the previous ranking are still present, “Wikipedia” now being at the first rank, while the other half were previously at a rank higher than 10th (BLEU, MATLAB, AnCora) or were not considered in the LRE Map, being posterior to 2012 (Word2Vec, Glove). We also see that a language resource such as Word2Vec was immediately adopted by many authors on the very same year when it appeared first in a paper of the NLP4NLP+5 corpus.

Table 30 provides over the past 20 years (2000 to 2020) the number of mentions of the different language resources from the LRE Map together with the number of documents that were published and the list of the 10 most cited language resources on that year. We see in the recent years, the increase of language resources related to machine learning and neural networks (Word2Vec, Weka, Glove, Keras, Seq2Seq, ROBERTa), as well as to the use of metrics (BLEU and now ROUGE) and the appearance of new speech corpora (LibriSpeech, SquaD).
Language Resource Impact Factor
We proposed to define the “Impact Factor” of a language resource as its existence, in recognition of the importance of the corresponding language resources for conducting research in NLP and of the researchers who provided these useful language resources, similar to the role of a citation index. Table 31 provides the impact factors for the language resources of the “Data,” “Evaluation,” and “Tools” types. We can notice the importance of quality measures (BLEU introduced for machine translation and ROUGE for text summarization) and of the recent burst of machine-learning toolkits (Word2Vec, GloVe, Weka, Seq2seq).

Text Reuse and Plagiarism
Here we studied the reuse of the textual content of NLP4NLP+5 papers in other NLP4NLP+5 papers (Mariani et al., 2016, 2018a).

Data
We considered here 88,752 documents published by 66,995 authors from 1965 to 2020, which constitute a large part of the published articles in the field of SNLP, apart from the workshop proceedings and the published books.

The preparation of the textual data is described in the study of Francopoulo et al. (2015b). The overall number of words is roughly 380 MWords. Only the texts in English and French have been retained.

Algorithm for Computing Papers Similarity
The detection of “copy & paste” as defined in Appendix 5 is conducted through an algorithm described in the study of Mariani et al. (2019b). The comparison is conducted on a window of seven tokens, using the Jaccard distance and a threshold of 0.04. We therefore consider as potentially reused or plagiarized all couples of articles with a similarity score of 4% or more according to our measure of similarity.

Categorization of the Results
Our previous experiments showed that it is necessary to carefully check the results as it may contain false alarms due to the presence of short texts, such as acknowledgments, or of truncated
| Rank 2020 | Rank 2015 | Name | Type | # Existences | # Occurrences | First author | First corpora | First year | Last year |
|-----------|-----------|------|------|--------------|--------------|--------------|--------------|------------|-----------|
| 1         | 3         | Wikipedia | NLPCorpus | 6,348 | 36695 | Ana Licuanan, Jinxi Xu, Ralph M. Weischedel | trec | 2003 | 2020 |
| 2         | 1         | WordNet | NLPLexicon | 5,803 | 37654 | Kenji Sakamoto, Kouichi Yamaguchi, Yoshiji Fujimoto | isca | 1990 | 2020 |
| 3         | 2         | BLEU | NLPSpecification | 4,595 | 42311 | Ludovic Lebart | modulad | 2001 | 2020 |
| 4         | 2         | Timit | NLPCorpus | 3,982 | 15984 | Andrej Ljolje, Benjamin Chigier, David Goodine, David S. Pallett, Erik Urdang, Fileno Alteva, Francine R. Chen, George R. Doddington, Hong C. Leung, Hsiao Wuen Hon, James L. Hieronymus, James R. Glass, Jan Robin Rohlicek, Jeff Shriber, Jeffrey N. Marcus, John Dowding, John F. Prett, John S. Garofolo, Joseph H. Polifroni, Judith R. Spitz, Julia B. Hirschberg, Kai Fu Lee, L. G. Miller, Mark Liberman, Myeong Hwang, Michael D. Riley, Michael S. Phillips, Robert Weide, Stephanie Senet, Stephen E. Levinson, Vassilios V. Digalakis, Victor W. Zue | hlt, isca, taslp | 1989 | 2020 |
| 5         | 4         | Penn Treebank | NLPCorpus | 2,786 | 10,622 | Beatrice Santorini, David M. Magearman, Eric Brit, Mitchell P. Marcus | acl, coling, conll, eacl, emnlp, ipec, sem, tacl, trec | 1990 | 2020 |
| 6         | 2         | Word2Vec | NLPTool | 2,536 | 8,245 | Allan Hanbury, Amir Globerson, Angelina Ivanova, Baobao Chang, Bin Gao, Binqin, Bo Tang, Brigitte Grau, Bruno Martini, Bryan Rink, Carina Silberer, Carlos Guestrin, Carmen Banea, Chengqiong Zong, Christopher D. Manning, Chuchu Huang, Claire Cardie, Cícero Nogueira Dos Santos, Cícero Nogueira Dos Santos, D. Song, Dakun Zhang, Daniel Zeman, Daniel P. Flickinger, Danqi Chen, David B. Bracewell, Daxiang Dong, Denz Yuret, Di Chen, Dinhai Yu, Dimitri Kartsaklis, Duyu Tang, Emanuela Boros, Enhong Chen, Fabian Shi, Fei Tian, Filip Ginter, Furu Wei, Georgiana Dinu, Germán Kruszewski, Guan Chen, Guoxin Cui, Haiqiang Wang, Haiyang Wu, Hal Daume III, Hanjun Dai, Heike Adel, Hinrich Schütze, Hu Junfeng, Hua Wu, Idan Szpektor, Ido Dagan, Ignacio Cano, Ion Androutsopoulos, Ivan Títov, Jacob Goldberger, Jan Hajic, Janycha M. Webe, Jason Weston, Jeffrey Pennington, Jenna Kanerva, Jiajun Zhang, Jiang Bian, Jiang Guo, Jianlin Feng, Jianwen Zhang, Johannes Bjerva, John Papadopoulos, Jordan Boyd Graber, João Filgueiras, João Palotti, Jiaqi Luotolahti, Jun Zhao, Jun Cheng Guo, Kai Hakala, Kang Liu, Karen Livescu, Kazuma Hashimoto, Keith Adams, Kevin Gimpel, Leonid Andronov, Li Dong, Liuheng Xu, Linda Anderson, Liuming Jiang Xiao, Maria Gatti, Makoto Miwa, Malvina Nissim, Maozong Sun, Marc Tomlinson, Marco Baroni, Marco Kuhlmann, Marek Rei, Mark Dredze, Matthew Purver, Mehrnoosh Sadrozadeh, Michael Mohler, Miguel B. Almeida, Mikhail Kozhevnikov, Ming Zhou, Mirella Lapata, Mo Yu, Mohit Bansal, Mohit Iyer, Mu Li, Mario J. Silva, Nan Yang, Navid Rekabsaz, Nianwen Xue, Olivier Ferret, Omer Levy, Oren Melamud, P. Zhang, Peng Hsuan Li, Peter Ennix, Philip Resnik, Pontus Stenetorp, Qinlong Wang, Rada F. Mihalcea, Regina Barzilay, Richard Socher, Rob Van Der Goot, Romaric Besançon, Rui Zhang, Sameer Singh, Sandra Maria Harabagiu, Shaodong He, Shizhu He, Shujie Liu, Silvio Amir, Stephan Oepen, Sumit Chopra, Swidiya Kayestha, Tae Go, Ta Li, Tatsuya Izu, Ted Briscoe, Tie Yan Liu, Ting Liu, Travis R. Goodwin, Wanxiang Che, Wei He, Weirn Xu, Wen Ting Wang, Wenzhe Pei, Xiaobin Hao, Xianqiang Hu, Xiaojun Zou, Xiaolei Lu, Xiaohao Zhao, Xingpeng Zhang, Xinxiu Chen, Yueke Xu, Xueqi Cheng, Yang Liu, Yi Zhang, Yoav Goldberg, Yonatan Belkin, Yongjiang Chen, Yoon Chul Kim, Yoshimitsu Tsuruoka, Yuanjuan Qi, Yuanzhe Zhang, Yuchen Zhang, Yue Liu, Yusuke Miyao, Yuta Tsuibo, Zhen Wang, Zheng Chen, Zhenjun Tang, Zhiqiang Toh, Zhiyuan Liu | acl, coling, conll, eacl, emnlp, ipec, sem, tacl, trec | 2014 | 2020 |
| 7         | 5         | Praat | NLPTool | 2,123 | 4,359 | Carlos Gussenhoven, Toni C. M. Rietveld | isca | 1997 | 2020 |
| 8         | 10        | MATLAB | NLPTool | 1,915 | 2,842 | Demosthenis Stavrini, Michael D. Zoeteweii | taslp | 1989 | 2020 |
| 9         | 10        | GloVe | NLPTool | 1,863 | 6,686 | Christopher D. Manning, Jeffrey Pennington, Richard Socher | emnlp | 2014 | 2020 |
| 10        | 10        | Ancora | NLPCorpus | 1,694 | 3,233 | Barbara J. Grosz, Jaime G. Carbonell, Mitchell P. Marcus, Ralph M. Weischedel, Raymond Perrault, Robert Wilensky, Wendy G. Lehnert | hlt | 1989 | 2020 |
In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data. In many cases, the author appears with a different spelling, or references are properly quoted, but with a different wording, or merged documents due to OCRization for the eldest data.

The detection of the authors’ name ensures a good reliability for the “self-reuse” and “self-plagiarism” categories. For each of the 4 copy and paste categories, we produced the list of couples of “similar” papers according to our criteria, with their similarity score, identification of the common parts, and indication of a similar list of authors or of the same title.

Results on NLP4NL-P+5
We do not include in this paper the matrices for each of the four categories (self-reuse, self-plagiarism, reuse, and plagiarism) displaying the number of papers that are similar for each couple of the 34 sources (considered as “using sources” and “used sources”) that were presented in our previous paper, as they do not show a large difference with the previous findings. On the 13,068 cases detected using the NLP4NL-P+5 corpus, 5,799 (44%) are identified as self-reuse, 6,942 (53%) as self-plagiarism, 152 (1.5%) as reuse, and 175 (1.3%) as plagiarism.

Figure 53 provides the percentage of papers that are detected as using parts of other papers over the years, whereas Figure 54 provides the percentage of papers that are detected as having been used by other papers over the years, given that they almost entirely correspond to self-reuse and self-plagiarism.

As it clearly shows, self-reuse and self-plagiarism keep being very common: about 25% of papers use parts of previous papers, whereas parts of 25% of papers are used in a new paper. This may also be related to the submission of similar papers at two different conferences on the same year, or to the publication in a journal of a paper previously published in a conference.
Just as noticed in our previous NLP4NLP study, the reuse of papers is done within a short time period (on the same year in 40% of the cases, and within 2 years in 85% of the cases). The reuse of conference papers in journal articles is done with a slightly longer delay (on the same year in 11% of the cases, and within 3 years in 84% of the cases).

**Plagiarism**

We characterized plagiarism by authors using in a paper a large part (more than 4%) of textual content from a paper of other authors without citing the source paper.

In our previous study related to publications up to 2015, 116 cases of possible plagiarisms were detected over 50 years on a total of 63,357 papers (less than 0.4%), which reduced to only one case with a 10% similarity score after a careful manual checking made possible by the small number of detected cases, as described in the study of Mariani et al. (2019b).

From 2015 to 2020, 47 cases of possible plagiarism are detected on a total of 20,649 papers, which also reduce to a single case after a careful manual checking! In addition to the various reasons for the false detection of plagiarism identified in our previous study, we also found out that a paper may be identified as plagiarizing another paper, whereas the authors of that other paper actually plagiarize themselves a former paper of the previous authors!

**CONCLUSIONS**

When comparing the study contained in this paper with the findings of our two previous papers, we may first consider the results that reinforce on 55 years the conclusions that we made on 50 years.
As already encountered while pursuing the study reported in our previous papers, we appreciated the benefit to have access to a large quantity of publications that are now freely accessible online, while we faced the difficulty of dealing with proprietary data which requires extensive discussions with the publishers to explain the nature of our investigations that necessitates a large collection of papers. It also raises the problem of distributing the data, replicating the results and updating the corpus.

We still struggled with the lack of a consistent and uniform identification of entities (titles, authors names, gender, affiliations, conference and journal names, funding agencies, names of language resources, etc.), which required a tedious manual correction process. This problem would need an international effort to provide unique identifiers to these entities, or else sophisticated disambiguation processes.

We also see that there is less and slow progress in the feminization of the research community.

This study confirmed the possibility to predict some future scientific developments for the next 3 years.

The study of reuse and plagiarism still concludes in the scarcity of real plagiarism cases, a conclusion which, however, needs a careful manual checking in addition to any automatic process, and in the commonness of the reuse of previously published textual content by the same authors which is very widespread and easily understandable, especially when turning a conference paper into a journal article.

While confirming these previous findings, this study also illustrates the tremendous changes in the speech and natural language processing community that happened during the past 5 years.

We first notice a very intense research activity reflected by a huge increase in the number of papers and authors, similar in the single year 2020 to what occurred in the first 25 years of our corpus.

More and more collaborations took place among authors, who formed new clusters. Important changes appear in the ranked list of the most productive, most collaborative, most cited, and best h-indexed authors, with the appearance of many new names, especially of Asian origins, who publish a lot, while many researchers of the pioneering times are now gradually retiring. Also, it seems that slightly more focus is nowadays devoted to NLP compared to speech processing where many breakthroughs have already been achieved in the recent past and which now shares many scientific challenges and many similar approaches in common with NLP.

This is due to the appearance of new paradigms, such as deep learning, word embedding, or unsupervised machine learning, which immediately attracted a large community of researchers, due to the acceleration in publishing, who increasingly publish in conferences and journals either within NLP4NLP, where we notice a specific increase in activity for the Transactions of the ACL, or outside of the NLP4NLP core research area and publications, especially in arXiv which now appears as a popular free open-access not-peer-reviewed publication facility.

The use of language resources is also increasing a lot, according to the crucial need of data in machine-learning approaches for developing and improving the quality of systems related to a language, a population or a task, and of proper metrics to measure quality and progress. New language resources of various kinds (dataset, tools, metrics) specifically related to these paradigms became quickly very popular.

Some research domains were initiated or reactivated, such as semantic analysis, sentiment analysis, speech translation, or processing of low-resourced languages.

PERSPECTIVES

We would like to improve the quality of the automatic extraction of information (such as authors’ names, references, sources, terms, language resources) to reduce the burden of manual corrections by taking into account the context through novel approaches of disambiguation based on word embedding.

We believe that the raw data that we gathered and the information that we extracted after substantial manual cleaning would provide interesting training and test data for evaluation campaigns (such as automatic name extraction, named entity disambiguation or gender detection).

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: http://www.nlp4nlp.org.

AUTHOR CONTRIBUTIONS

JM coordinated the production and writing of the paper. GF produced the corpus and developed the software packages. PP provided specific analyses and regular advices. FV developed the GapChart visualization tool. All authors contributed to the article and approved the submitted version.

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Conflict of Interest: GF was employed by Tagmatica.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix 1: Acknowledgments

The authors wish to thank the ACL colleagues, Ken Church, Sanjeev Khudanpur, Amjad Abu Jbara, Dragomir Radev, and Simone Teufel, who helped them in the starting phase, Isabel Trancoso, who gave her ISCA Archive analysis on the use of assessment and corpora, Wolfgang Hess, who produced and provided a 14 GBytes ISCA Archive, Emmanuelle Foxonet who provided a list of authors’ given names with the genre, Florian Boudin, who made available the TALN Anthology, Helen van der Stelt and Jolanda Voogd (Springer) who provided the LRE data and Douglas O’Shaughnessy, Denise Hurley, Rebecca Wollman, Casey Schwartz, Dilek Hakkani-Tür, Kathy Jackson, William Colachio and Shirley Wisk (IEEE) who provided the IEEE ICASSP and TASLP data. They also thank Khalid Choukri, Alexandre Sicard, Nicoletta Calzolari, Riccardo del Gratta, Sara Goggi, and Gabriella Pardelli who provided information about the past LREC conferences and the LRE Map, Victoria Arranz, Ioanna Giannopoulou, Johann Gorlier, Jérémy Leixa, Valérie Mapelli, and Hélène Mazo, who helped in recovering the metadata for LREC 1998, Nancy Ide and Christopher Cieri for their advice and all the editors, organizers, reviewers and authors over those 55 years without whom this analysis could not have been conducted!

Appendix 2: Apologies

This survey has been made on textual data, which covers a 55-year period, including scanned content. The analysis uses tools that automatically process the content of the scientific papers and may make errors. Therefore, the results should be regarded as reflecting a large margin of error. The authors wish to apologize for any errors the reader may detect, and they will gladly rectify any such errors in future releases of the survey results.

Appendix 3: Relationship With Other Papers and Reuse of Previous Material

The present paper is the follow up of a series of two papers:

- Mariani et al. (2019a). The NLP4NLP Corpus (I): 50 Years of Publication, Collaboration, and Citation in Speech and Language Processing
- Mariani et al. (2019b). The NLP4NLP Corpus (II): 50 Years of Research in Speech and Language Processing,

which appeared in the same special issue on “Mining Scientific Papers: NLP-enhanced Bibliometrics” of the Frontiers in Research Metrics and Analytics journal, edited by Iana Atanassova, Marc Bertin, and Philipp Mayr.

Appendix 4: Collaboration and Citation Graphs Terminology

Definitions of a collaboration graph as a model of social network and on the various structures and measures (nodes, edges, connected component, giant component, cliques, collaboration distance, collaboration path, diameter, degree of a node, clustering coefficient, density, etc.) are given in Mariani et al. (2018a). We assessed the position of each author in the Collaboration Graph according to various kinds of centrality: Closeness centrality, also called harmonic centrality (average closeness distance of an author with all other authors belonging to the same connected component), degree centrality (number of different co-authors of each author, i.e. the number of edges attached to the corresponding node), betweenness centrality [number of paths crossing a node, which reflects the importance of an author as a bridge across different sets of authors (or sub-communities)]. We also defined citing and cited papers and authors citation graphs and their structure and measures (strongly connected components, symmetric strongly connected components, citation distance, diameter, degree of a node, average clustering coefficient, density, etc.) (Mariani et al., 2018a). We studied the four Citing and Cited/Authors and Papers Graphs for each of the 34 sources, either internally to the source or in the context of the NLP4NLP+5 corpus, for the authors:

- the citation by the source authors of the source authors (“Internal Authors Citations”),
- the citation by the source authors of NLP4NLP+5 authors (“Outgoing Global Authors Citations”),
- the citation by NLP4NLP+5 authors of the source authors (“Ingoing Global Authors Citations”).

and for the papers:

- the citation in the source papers of the same source (“Internal Papers Citation”),
- the citation in the source papers of NLP4NLP+5 papers (“Outgoing Global Papers Citation”),
- the citation in NLP4NLP+5 papers of the source papers (“Ingoing Global Papers Citations”).

Appendix 5: “Copy and Paste” Terminology

As the terminology is fuzzy and contradictory among the scientific literature, we first defined four types of “copy & paste” (Table A1):

- “self-reuse” when the source of the copy has an author who belongs to the group of authors of the text of the paste and when the source is cited.
- “self-plagiarism” when the source of the copy has an author who belongs to the group of authors of the text of the paste, but when the source is not cited.
- “reuse” when the source of the copy has no author in the group of authors of the paste and when the source is cited.
- “plagiarism” when the source of the copy has no author in the group of the paste and when the source is not cited.

| Source is quoted | Source is not quoted |
|------------------|---------------------|
| At least one author in both papers | Self-Reuse | Self-Plagiarism |
| No author in common | Reuse | Plagiarism |