# Development of Domains and Keyphrases along Years

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Keywords: Development Concepts, Development Model, NLP Domains, Keyphrases, Trends, Word Bigrams and Trigrams.

Abstract: This paper presents a methodology (including a detailed algorithm, various development concepts and measures, and stopword lists) for measuring the development of domains and keyphrases along years. The examined corpus contains 1020 articles that were accepted for full presentation in PACLIC along the last 18 years. The experimental results for 5 chosen domains (digital humanities, language resources, machine translation, sentiment analysis and opinion mining, and social media) suggest that development trends of domains and keyphrases can be efficiently measured. Top bigrams and trigrams were found as efficient to identify general trends in NLP domains.

## 1 INTRODUCTION

Your Natural language processing (NLP) is the research and application domain that investigates how computers and software can be used to successfully process natural language text or speech. NLP contains a wide range of research fields, e.g.: information extraction, information retrieval, machine learning, machine translation, morphology, natural language generation, phonology, semantics, sentiment analysis, syntax, speech recognition, and summarization.

NLP is a very active research domain. Many conferences (e.g., ACL, CICLing, COLING, CONLL, EMNLP, LREC, NAACL, and PACLIC) are held in this area every one or two years. Thousands of academic works are published every year in various forums of NLP such as journals, conferences, workshops, symposiums, Ph.D. dissertations, M.Sc. theses, technical papers, and working papers.

Among the research issues that are covered by NLP is the investigation of the development of various NLP's sub-domains in general and their keyphrases in particular over the years. An example for such a question is the analysis of the development of domains and keyphrases in various NLP's conferences over the years.

The aim of this work is to explore a corpus of a certain NLP conference and to analyze the development of the NLP's keyphrases and domains along an interval of years. The chosen application domain is the articles of the Pacific Asia Conference on Language, Information and Computation (PACLIC) that were accepted for full presentation along the last 18 years (1998-2015). For this study we decided to investigate five research domains: (1) digital humanities, (2) language resources, (3) machine translation, (4) sentiment analysis and opinion mining, and (5) social media. These domains were selected from the domain list that is provided in PACLIC-2016 (http://paclic30.khu.ac.kr/index.html).

The motivation of this research is to discover important trends in various domains and keyphrases in a given conference. The identification of such trends is important in order to know which domains are currently top or more important ones and which domains are less or no longer important. The findings might allow proper resource allocation on the one hand and a choice of "hot" research topics by researchers on the other hand. Furthermore, the identification of NLP's domains and their key-phrases will enable automatic classification of papers into NLP's domains. Such a classification can help journal editors and conference chairs to automatically distribute papers to suitable reviewers.

The rest of this paper is organized as follows: Section 2 presents relevant background about investigating research trends over years. Section 3



HaCohen-Kerner, Y. and Hassan, M.
Development of Domains and Keyphrases along Years.
DOI: 10.5220/0006077303750383
In *Proceedings of the 8th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2016) - Volume 1: KDIR*, pages 375-383
ISBN: 978-989-758-203-5

introduces various NLP's domains and development of domains and keyphrases. Section 4 describes the model that enables the exploring of the development of domains and keyphrases along the years. Section 5 presents the examined corpus, the experimental results and their analysis. Finally, Section 6 summarizes the main findings and suggests future directions.

## 2 INVESTIGATION OF RESEARCH TRENDS

Investigation of research trends or domains was conducted in a number of ways based on at least one of the following elements: citations, topics, keyphrases, and sentences.

### 2.1 Citations

There are many works that explored citations in scientific papers. Garfield (1965) was the first to publish an investigation of the issue of automatic production of citation indexes, extraction, and analysis of citations from documents. He found that citation indices can also be used to analyze research trends, identify emerging areas of science, and determine the popularity of an article.

Nanba and Okumura (1999) defined the concept of a citing area as the sequence of sentences that appear around the location of a given reference in a certain scientific paper. The authors also presented a rule-based algorithm to identify the citing area of any given reference. Later on, Nanba et al. (2000) used their algorithm to identify the author's reason for citing a given paper.

Radev and Abu-Jbara (2012) investigated citing sentences (a citing sentence is a sentence, which appears in a scientific paper and contains an explicit reference to another paper) that appear in the ACL Anthology Network (AAN, http://clair.eecs.umich.edu/anthology/), which is a comprehensive manually curated networked corpus of citations and collaborations in the field of computational linguistics. In their paper, the authors used the AAN in order to discover research trends and to summarize previous discoveries and contributions. In addition, they presented a few applications that make use of citing sentences e.g., identifying controversial arguments, identifying relations between techniques, tools and tasks, and scientific literature summarization.

Sim et al. (2012) presented a joint probabilistic model of who cites whom in computational linguistics, and also of how is the citing written. Their model reveals latent factions, which are groups of individuals whom we expect to collaborate more closely within their faction, cite within the faction using language distinct from citation outside the faction, and be largely understandable through the language used when cited from without. The authors conducted an exploratory data analysis on the ACL Anthology and they extended the model to reveal changes in some authors' faction memberships over time.

Research trends in scientific literature have been also investigated by many researchers (e.g., McCallum et al., 2006; Dietz et al., 2007; Hall et al., 2008; and Gerrish and Blei, 2010) using topic models such as the latent Dirichlet allocation (Blei et al., 2003) and its variations.

### 2.2 Topics

Exploring of computational history using topic models to analyze the rise and fall of research topics to study the progress of science, has been performed in general by Griffiths and Steyvers (2004) and more specifically in the ACL Anthology by Hall et al. (2008).

Anderson et al. (2012) developed a people-centered computational history of science that tracks authors over topics with application to the history of computational linguistics. The authors identified the topical subfields authors work on by assigning automatically generated topics to each paper in the ACL Anthology from 1980 to 2008. They identified four different research periods. They analyzed the flow of authors across topics to discern how some subfields flow into the next, forming different stages of ACL research. They claimed that the NLP's sub-domains become more integrated.

### 2.3 Keyphrases

Omodei et al. (2014A) presented a new method to extract keywords from texts and classify these keywords according to their informational value, derived from the analysis of the argumentative goal of the sentences they appear in. The method is applied to the ACL Anthology corpus, containing papers on the computational linguistic domain published between 1980 and 2008. The analysis of the ACL Anthology corpus is based on the identification of keywords, which are classified according to their informational status. The classification is done according to a text zoning analysis of the papers' abstracts. The authors showed that coupling keyword extraction with text zoning enable to observe fine grained facts in the dynamics of a scientific domain. Their approach allows to highlight interesting facts concerning the evolution of the topics and methods used in computational linguistics.

Daudaravičius (2012) employed collocation segmentation to extract terms from the ACL Anthology Reference Corpus. The results of his research show that until 1986, the most significant terms were related to formal/rule based methods. Since 1987, terms related to statistical methods (e.g., language model, similarity measure, and text classification) became more important. Since 1990, terms related to newly released language resources (e.g., Penn Treebank, Mutual Information, statistical parsing, bilingual corpus, and dependency tree) became the most important. There are some terms such as "machine translation" and "machine learning" that are significant throughout the whole ACL ARC corpus and they are not significant for any particular time period. That is to say, finding shows that some terms can be globally significant while some other terms are significant during part(s) of the time and insignificant during other part(s) of the time.

Omodei et al. (2014B) analyzed the evolution of the computational linguistics domain between the years of 1988 and 2012 using a quantitative analysis of the ACL Anthology. They reconstructed the socio-semantic landscape of the domain by inferring a co-authorship and a semantic network from the analysis of the corpus. Keywords were extracted using a hybrid approach mixing linguistic patterns with statistical information; then, the semantic network was built using a co-occurrence analysis of these keywords within the corpus. Combining temporal and network analysis techniques, their model is able to examine the main evolutions of the domain and to identify the active subdomains over the years.

## 2.4 Sentences

Reiplinger et al. (2012) introduced a comparative study of two approaches to extracting definitional sentences from a corpus of scholarly discourse: one based on bootstrapping lexico-syntactic patterns and another based on deep analysis. Computational linguistics was used as the target domain and the ACL Anthology as the corpus. Definitional sentences extracted for a set of well-defined concepts were rated by domain experts. Results show that both methods extract high-quality definition sentences intended for automated glossary construction. The majority of the extracted sentences provide useful information about the domain concepts. The authors claim that since both approaches use generic linguistic resources and pre-processing (identity extraction, name, POS-tagging, etc.) they can be considered domain-independent.

# 3 NLP'S DOMAINS AND KEYPHRASES AND THEIR DEVELOPMENT

## 3.1 NLP's Domains

There is no consensus among NLP's researchers about the division of NLP into research domains and their definitions. Each NLP's conference has its own division to NLP's sub-domains. PACLIC-2016 (http://paclic30.khu.ac.kr/index.html) presents the following list of sub-domains:

- Language Studies: Corpus linguistics, Discourse analysis, Language acquisition, Language learning, Language mind and culture, Language theory, Morphology, Phonology, Pragmatics/Sociolinguistics, Semantics, Spoken language processing, Syntax, Typology
- Information Processing and Computational Applications: Cognitive modeling of language, Dialogue and interactive systems, Digital humanities, Information retrieval/extraction, Language resources, Machine learning/Data mining, Machine translation, Multi-linguality in NLP, NLP applications, Sentiment analysis and opinion mining, Social media, Text classification/summarization, Word segmentation

## 3.2 Development of Domains and Keyphrases

We plan to investigate the life of several research domains in general and of several top frequent keyphrases in these domains in particular throughout the years of a certain conference. We would like to define concepts such as birth/death/rise/decline and to analyze their values for a certain conference.

Since our main research domain is NLP, we decided to apply our plan to an NLP conference and we chose to work on the articles that were accepted to PACLIC for full presentation along the last 18 years (1998-2015).

The chosen keyphrases are bigrams and trigrams (see Section 4 why unigrams are not regarded as keyphrases that identify domains). We intend to measure the development of a few selected domains and part of the keyphrases over groups of three years for each group. For this purpose, we defined the following measures of development:

- **Birth of a Keyphrase** – A keyphrase that did not appear in the past and its current frequency is above the minimal threshold (two appearances in a group of three years).

- **Death of a Keyphrase** - keyphrase that appeared in the past and its current frequency is 0.
- **Local Rise of a Keyphrase** - keyphrase that its value has increased relatively to its previous value.
- **Global Rise of a Keyphrase** - keyphrase that its last value has increased relatively to its first value.
- **Local Decline of a Keyphrase** - keyphrase that its value has decreased relatively to its previous value.
- **Global Decline of a Keyphrase** - keyphrase that its last value has decreased relatively to its first value.

Similar concepts (birth/death/rise/decline) can be defined for each domain based on the sum total values of the domain's top frequent n-grams.

## 4 THE DEVELOPMENT MODEL

The main stages of the development model are:

A. Creating a corpus including PDF-files representing an NLP conference. We then used a conversion program (http://www.squarepdf.net/file/get/6463hkb5ergbvkwaiq663zijza) to convert the PDF files of the source articles into text files.

B. Filtering stopwords and finding the best n-grams that represent each chosen domain using most-cited related papers (not necessarily PACLIC's papers). We decided to work only with 10 top bigrams and 3 top trigrams but without unigrams. According to our experiments, unigrams are not suitable for domain identification because many of them are ambiguous in the sense that they are suitable for more than one domain. Examples of such noisy unigrams are: "analysis", "corpus", "data", "feature", "features", "sentence", "text", "texts", "user", "users", and "web". Some of these unigrams can be added to the "domain stopwords". However, we did not do that because some of these unigrams might be parts of beneficial bigrams or trigrams.

C. Finding the frequencies of the top five frequent bigrams and the top frequent trigram for each group of 3 years for the last 18 years of the PACLIC's conference (1998-2015).

D. Computing the development trends of each chosen domain and its top n-grams over the years using the total values of the selected bigrams and trigram.

Analysis of the results of various bigrams, trigrams, and domains.

Each main stage will be detailed separately, as follows. In stage A, we selected five specific domains in NLP. These domains were chosen from the list of the domains that are belonging to the "Information Processing and Computational Applications" area. The five chosen domains are: (1) Digital humanities (DH), (2) Language resources (LR), (3) Machine translation (MT), (4) Sentiment analysis and opinion mining (SA & OM), and (5) Social media (SM).

For each domain, we extracted 50 papers via Google Scholar (https://scholar.google.com/). We downloaded only the 50 most-cited papers that contained in their headlines the exact keyphrase of their domain and we succeeded to achieve their PDF-version. That is to say, we downloaded the 50 most-cited papers that contained in their headlines "Digital humanities" and we were able to achieve their PDF-version. For the domain of "Sentiment analysis and opinion mining" we downloaded 25 papers that contained in their headlines "Sentiment analysis" and 25 papers that contained in their headlines "opinion mining".

For each one of these five domains using the 50 downloaded papers, we have extracted the ten most frequent bigrams and the three most frequent trigrams excluding stopwords. We chose these relatively low numbers of n-grams in order to avoid unnecessarily large number of n-grams on the one hand, and to avoid noisy n-grams that might be related to more than one domain on the other hand. We chose only 3 trigrams less than the number of chosen bigrams (10) because according to our experience there are much more frequent bigrams than frequent trigrams both in numbers and their frequencies. In other words, word bigrams are better representative classifiers for domain classification than word trigrams.

In stage B, we worked with PACLIC's papers using the top five frequent bigrams (out of the ten bigrams extracted from Google Scholar's papers) and the most frequent trigram (out of the three trigrams extracted from Google Scholar's papers) for each group of 3 years for each domain separately. We did not work with all the top n-grams that were extracted from Google Scholar because not all of these n-grams were included in PACLIC's papers.

Table 1: General information about the corpus.

| Total # of full papers | Total # of words | Avg. # of words per paper | Median value of words per paper | Std. of words per paper |
|---|---|---|---|---|
| 1020 | 5048544 | 4949.55 | 4905.5 | 1622.17 |

Table 2: General information about the corpus in units of groups of 3 years.

| Period of years | # of full papers | Total # of words | Avg. # of words per paper | Median value of words per paper | Std. of words per paper |
|---|---|---|---|---|---|
| 1998-2001 | 115 | 540113 | 4696.63 | 4506 | 1662.96 |
| 2002-2004 | 128 | 547378 | 4276.39 | 4223.5 | 1370.26 |
| 2005-2007 | 139 | 599036 | 4309.61 | 4110 | 1780.36 |
| 2008-2010 | 205 | 1031467 | 5031.55 | 4821 | 1299.6 |
| 2011-2013 | 239 | 1222014 | 5113.03 | 5152 | 1558.72 |
| 2014-2015 | 194 | 1108536 | 5714.10 | 5715 | 1586.77 |

The following procedure was applied in stage B:

1. All appearances of stopwords for general texts (called general stopwords) are deleted.
2. All appearances of stopwords for texts in NLP (called domain stopwords) are deleted.
3. All possible continuous N-gram words (for N =2, 3) are created, provided that the all the words in a certain N-gram are in the same sentence.
4. The frequency of each N-gram feature in the corpora is counted.
5. The bigram and trigram features (each group alone) are sorted in descending order.

There are 386 general stopwords, e.g., "a", "an", "and", "another", "any", "are", "aren't", "as", and "at". There are 606 domain stopwords, e.g., "abstract", "annual", "association", "chapter", "process", “processes", and "publishers".

**Measures Dealing with Development of Keyphrases**

We defined three measures to estimate the development of keyphrases. These measure will be described and discussed in the following paragraphs.

**Measure1 =** *# of occurrences of a certain keyphrase* in a certain period of time

The disadvantage of measure1 is that it does not take into account the # of papers that might be enlarged over the years. Assuming each period of time lasts one years, and for instance the # of a certain keyphrase can be increased from 50 to 60 in two consecutive years while the # of papers can be increased from 50 to 80 in the same two consecutive years. In other words, although it seems as if the frequency of a certain keyphrase has been increased, the truth is that the frequency of this certain keyphrase was decreased relatively to the increase of # of papers. Therefore, we thought about normalizing measure1 by the # of papers in the discussed year. This thought led to the definition of measure2.

**Measure2** = measure1 in a certain period of time / # of papers in the same period of time

Measure2 has also a serious disadvantage. It does not take into account specific situations. For example, a certain conference can decide that from a certain year the # of available pages for an accepted paper will be increased in two (e.g., from 8 to 10 pages). Thus, we thought about normalizing measure1 by the # of words included in all of the papers in the discussed period of time (call it the *# of words in the discussed period of time*). This thought led to the definition of measure3 as follows.

**Measure3** = 10000 * measure1 in a certain period of time / # of words in the discussed period of time

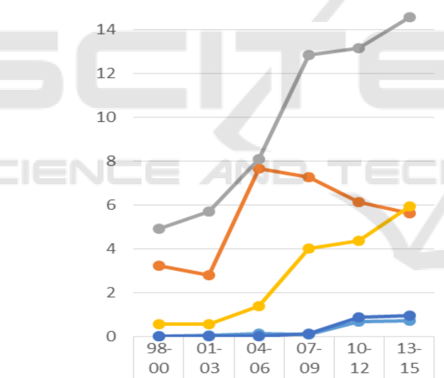
Measure3 is much more objective than the two previous measures. Thus, we decided to carry out our experiments using this measure. Since the results we received were very small numbers we decided to multiply each result by 10000.

# 5 CORPUS AND EXPERIMENTAL RESULTS

The examined corpus contains the articles of the Pacific Asia Conference on Language, Information and Computation (PACLIC) that were accepted for full presentation along the last 18 years (1998-2015). The PDF-versions of these papers were downloaded from the ACL Anthology web site. Table 1 presents general information about this corpus. Table 2 introduces various statistics while looking at the corpus in units of groups of 3 years for each group.

From Table 1 we see that along the last 18 years there were 1020 full papers and their average length is around 4950 words (very close to the median value ~ 4906 words). From Table 2 we see that in general the # of full papers is rising over the years starting from 115 papers in the first three years (1998-2000) and ending with 194 papers in the last three years (2013-2015). Also the average length of a paper in words in general is rising over the years starting from around 4500 words per paper in the first three years (1998-2000) and ending with around 5700 words per paper in the last three years (2013-2015).

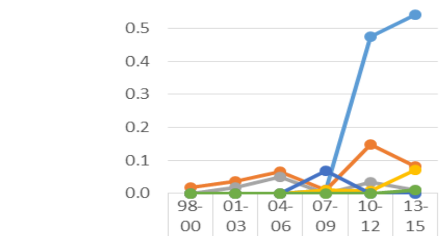
Figure 1 introduces the experimental results regarding the development of the five chosen domains according to the top five bigrams and the top first trigram for each domain along groups of 3 years. Figures 2-6 present the development of all the five selected domains; the development of each domain is presented alone based on its top five bigrams and its top first trigram. Figure 2 introduces the experimental results regarding the development of the DH domain according to its top five bigrams and its top first trigram along groups of 3 years.




| | 98-00 | 01-03 | 04-06 | 07-09 | 10-12 | 13-15 |
|---|---|---|---|---|---|---|
| DH | 0.02 | 0.05 | 0.12 | 0.10 | 0.66 | 0.71 |
| LR | 3.24 | 2.80 | 7.66 | 7.25 | 6.12 | 5.60 |
| MT | 4.93 | 5.70 | 8.08 | 12.86 | 13.14 | 14.56 |
| SA & OM | 0.56 | 0.57 | 1.37 | 4.02 | 4.38 | 5.92 |
| SM | 0.02 | 0.00 | 0.00 | 0.11 | 0.88 | 0.95 |

Figure 1: Domains' development along the years.

Figure 1 shows that in general there is a global rise for all the five domains because the last value of measure3 (years 13-15) of each domain is higher than the first value of measure3 (years 98-00). However, the values of the first three domains (LR, SA&OM, and MT) are significantly higher than the values of the last two domains (DH, and SM). This means that the first three domains (especially MT) are much more popular from the viewpoint of their top chosen features along the years than the last two

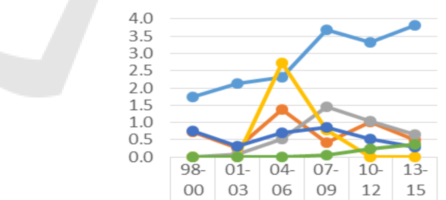



| | 98-00 | 01-03 | 04-06 | 07-09 | 10-12 | 13-15 |
|---|---|---|---|---|---|---|
| social media | 0.00 | 0.00 | 0.00 | 0.01 | 0.47 | 0.54 |
| social sciences | 0.02 | 0.04 | 0.07 | 0.01 | 0.15 | 0.08 |
| humanities research | 0.00 | 0.02 | 0.05 | 0.00 | 0.03 | 0.01 |
| digital humanities | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.07 |
| digital media | 0.00 | 0.00 | 0.00 | 0.07 | 0.00 | 0.00 |
| digital humanities research | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |

Figure 2: Development of the DH domain.

domains, especially over the last years. Moreover, the global rise of the first three domains is significantly higher in absolute values along the years than the last two domains. There are also several local declines. Most of them belong to the LR domain.

Figure 2 shows that only one bigram "social media" has a relative significant rise compared to the other top keyphrases. The values of most other keyphrases are close to zero over most of the years. These findings indicate that DH is not a popular research domain among PACLIC's full papers. Three keyphrases present a late birth during 07-09 (i.e., they had zero frequencies until 07).

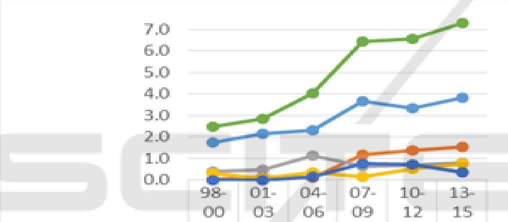



| | 98-00 | 01-03 | 04-06 | 07-09 | 10-12 | 13-15 |
|---|---|---|---|---|---|---|
| machine translation | 1.74 | 2.14 | 2.32 | 3.67 | 3.32 | 3.83 |
| speech recognition | 0.74 | 0.27 | 1.37 | 0.41 | 1.01 | 0.49 |
| language resources | 0.00 | 0.07 | 0.53 | 1.45 | 1.05 | 0.65 |
| sign language | 0.00 | 0.00 | 2.72 | 0.79 | 0.00 | 0.00 |
| spoken language | 0.76 | 0.31 | 0.72 | 0.87 | 0.52 | 0.28 |
| human language technologies | 0.00 | 0.00 | 0.00 | 0.06 | 0.23 | 0.36 |

Figure 3: Development of the LR domain.

Figure 3 introduces the experimental results regarding the development of the LR domain according to its top five bigrams and its top first trigram. Figure 4 introduces the experimental results regarding the development of the MT domain according to its top five bigrams and its top first trigram along groups of 3 years.

Figure 3 shows that the LR domain is a heterogeneous domain from the viewpoint of its top chosen n-grams. There are three keyphrases (“machine translation”, “language resources”, and “human language technologies”) that present a global rise over the years; while the other three keyphrases (“speech recognition”, “sign language”, and “spoken language”) present a global decline over the years. Moreover, the “sign language” keyphrase presents “death”. The most impressive rise was observed for the bigram “machine translation”, which is the name of another domain. Based on Figures 1 and 3, the LR domain seems as an important and unstable domain with a general increase over the years characterized also by a few declines in different periods of years.

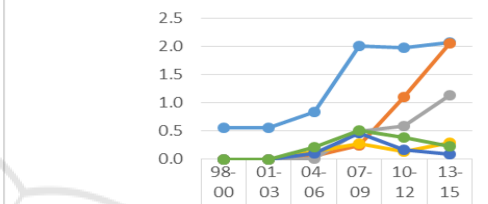



| | 98-00 | 01-03 | 04-06 | 07-09 | 10-12 | 13-15 |
|---|---|---|---|---|---|---|
| machine translation | 1.74 | 2.14 | 2.32 | 3.67 | 3.32 | 3.83 |
| statistical machine | 0.04 | 0.16 | 0.10 | 1.18 | 1.37 | 1.52 |
| target language | 0.39 | 0.49 | 1.14 | 0.65 | 0.66 | 0.80 |
| word alignment | 0.30 | 0.05 | 0.35 | 0.15 | 0.52 | 0.78 |
| translation quality | 0.00 | 0.00 | 0.13 | 0.78 | 0.70 | 0.35 |
| statistical machine translation | 2.46 | 2.85 | 4.04 | 6.43 | 6.57 | 7.28 |

Figure 4: Development of the MT Domain.

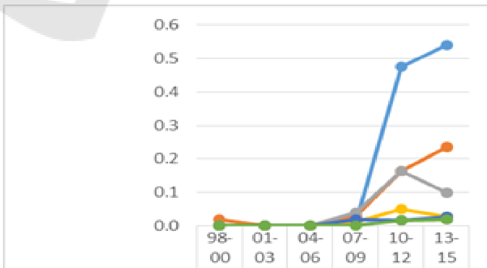
Figure 4 shows rises for all five MT’s keyphrases. The most impressive rise was observed for the trigram “statistical machine translation” starting from 2.46 and ending with 7.28; values higher the compatible values of all the five top bigrams over all the years. Moreover, the values obtained by the MT’s top three keyphrases (above 1.0) are higher than the values obtained by all the other keyphrases from all the other four domains (Figures 2, 3, 5, and 6). The same finding can be seen in Figure 1, where the values of MT’s keyphrases are much higher than those of all other four domains. Figure 5 introduces the experimental results regarding the development of the fourth domain SA & OM according to its top five bigrams and its top first trigram. Figure 6 introduces the experimental results regarding the development of the SM domain according to its top five bigrams and its top first trigram.

Figure 5 shows rises for all five SA&OM’s keyphrases likewise the MT domain (Figure 4). While three keyphrases (“opinion mining”, “semantic orientation”, and “conditional random fields”) present relatively small increases, the “machine learning” keyphrase presents an impressive jump from 04-06 to 07-09 and the two sentiment keyphrases “sentiment analysis” and “sentiment classification” present impressive increases over the last 6-9 years.




| | 98-00 | 01-03 | 04-06 | 07-09 | 10-12 | 13-15 |
|---|---|---|---|---|---|---|
| machine learning | 0.56 | 0.57 | 0.83 | 2.02 | 1.98 | 2.08 |
| sentiment analysis | 0.00 | 0.00 | 0.07 | 0.25 | 1.11 | 2.07 |
| sentiment classification | 0.00 | 0.00 | 0.02 | 0.49 | 0.60 | 1.14 |
| opinion mining | 0.00 | 0.00 | 0.13 | 0.28 | 0.13 | 0.30 |
| semantic orientation | 0.00 | 0.00 | 0.10 | 0.47 | 0.16 | 0.10 |
| conditional random fields | 0.00 | 0.00 | 0.22 | 0.51 | 0.39 | 0.23 |

Figure 5: Development of the SA&OM domain.




| | 98-00 | 01-03 | 04-06 | 07-09 | 10-12 | 13-15 |
|---|---|---|---|---|---|---|
| social media | 0.00 | 0.00 | 0.00 | 0.01 | 0.47 | 0.54 |
| social networks | 0.02 | 0.00 | 0.00 | 0.03 | 0.16 | 0.23 |
| social network | 0.00 | 0.00 | 0.00 | 0.04 | 0.16 | 0.10 |
| social networking | 0.00 | 0.00 | 0.00 | 0.01 | 0.05 | 0.03 |
| internet users | 0.00 | 0.00 | 0.00 | 0.02 | 0.02 | 0.03 |
| social media users | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.02 |

Figure 6: Development of the SM Domain.

Figure 6 shows very small rises for three SM's keyphrases ("social networking", "internet users, and "social media users"). Only two keyphrases "social media" and "social networks" show relatively nice rises. It is interesting to point that four out of the five keyphrases include the word "social", which is also the dominate word included in the domain name. The relatively low values of all the five keyphrases are compatible with the low scores of this domain in Figure 1.

# 6 SUMMARY AND FUTURE WORK

In this paper, we present a methodology (including a detailed algorithm, various development measures, and suitable stopword lists) for measuring the development of domains and keyphrases. The experimental results suggest that development trends of domains and keyphrases can be efficiently measured using measure3.

The main findings are: (1) The investigation of the five NLP sub-domains found that three domains: LR, SA&OM, and especially MT are much more popular especially over the last years, while DH and SM are significantly less explored; (2) Top bigrams and trigram(s) are enough to identify general trends in NLP domains while unigrams are noisy and therefore were avoided; and (3) As expected the name of the domain was one of the top keyphrases in each one of the tested domain.

Future research proposals are: (1) Use extended definitions of keyphrases (not only bigrams and trigrams) and apply more sophisticated methods to automatically learn and extract keyphrases (e.g., HaCohen-Kerner et al, 2005; HaCohen-Kerner et al, 2007); (2) Apply additional keyphrases' measures, which are more complex and informative such as PWI "probability-weighted amount of information'' and TF-IDF ''Term frequency–inverse document frequency''; (3) Perform additional experiments on other kinds of intervals of years (e.g., every one year, every five years); (4) Apply this development model to other types of NLP domains and conferences as well as to other domains in other fields; and (5) Investigation of additional concepts regarding development of domains and concepts such as merge of two concepts (domains) to one concept (domain), and split of one concept (domain) to several concepts (domains).

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