A peer-reviewed version of this preprint was published in PeerJ on 19 June 2017.

Salatino AA, Osborne F, Motta E. 2017. How are topics born? Understanding the research dynamics preceding the emergence of new areas. PeerJ Computer Science 3:e119
https://doi.org/10.7717/peerj-cs.119

How Are Topics Born? Understanding the Research Dynamics Preceding the Emergence of New Areas.

Angelo Antonio Salatino, Francesco Osborne, Enrico Motta

Knowledge Media Institute, The Open University, Milton Keynes, UK

Corresponding Author: Angelo Antonio Salatino

Email address: angelo.salatino@open.ac.uk

PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.2306v3 | CC BY 4.0 Open Access | rec: 30 Nov 2016, publ:

ABSTRACT

The ability to recognise new research trends early is strategic for many stakeholders, such as academics, institutional funding bodies, academic publishers and companies. While the state of the art presents several works on the identification of novel research topics, detecting the emergence of a new research area at a very early stage, i.e., when the area has not been even explicitly labelled and is associated with very few publications, is still an open challenge. This limitation hinders the ability of the aforementioned stakeholders to timely react to the emergence of new areas in the research landscape. In this paper, we address this issue by hypothesising the existence of an embryonic stage for research topics and by suggesting that topics in this phase can actually be detected by analysing diachronically the co-occurrence graph of already established topics. To confirm our hypothesis, we performed a study of the dynamics preceding the creation of novel topics. This analysis showed that the emergence of new topics is actually anticipated by a significant increase of the pace of collaboration and density in the co-occurrence graphs of related research areas. These findings are very relevant to a number of research communities and stakeholders. Firstly, they confirm the existence of an embryonic phase in the development of research topics and suggest that it might be possible to perform very early detection of research topics by taking into account the aforementioned dynamics. Secondly, they bring new empirical evidence to related theories in Philosophy of Science. Finally, they suggest that significant new topics tend to emerge in an environment in which previously less interconnected research areas start cross-fertilising.

Keywords: Scholarly Data, Empirical Study, Research Trend Detection, Topic Emergence Detection, Topic Discovery, Digital Libraries, Ontology, Semantic Web

INTRODUCTION

Being aware of the rise of new research topics can bring significant benefits for anybody involved in the research environment. Academic publishers and editors can exploit this knowledge and offer the most up to date and interesting contents. Researchers might be interested in new trends related to their topics and in promising new research areas. Institutional funding bodies and companies need to be regularly updated on how the research landscape is evolving in order to make early decisions about critical investments. Nonetheless, considering the growth rate of research publications (Larsen & Von Ins 2010), keeping up with novel trends is a challenge even for expert researchers and traditional methods, such as the manual exploration of publications in significant conferences and journals, are no longer viable. This has led to the emergence of several approaches capable of detecting novel topics and research trends (Bolelli et al. 2009; Duvvuru et al. 2012; He et al. 2009; Wu et al. 2016). However, these approaches focus on topics that are associated with a substantial number of publications or on which the scientific community has reached a consensus for a specific label. This limitation hinders the ability of aforementioned stakeholders to react promptly to new developments in the research landscape.

We thus need novel methods for identifying the appearance of new topics at a very early stage, assessing their potential and forecasting their trend. To this end, we must achieve a better understanding of the dynamics underlying the creation of new topics and how these can be detected using current knowledge bases.

Philosophy of Science offers a number of interesting theories about the emergence of new topics. Kuhn (2012) theorised that science evolves through paradigm shifts. According to him, scientific work is performed within a set of paradigms and when these paradigms cannot cope with certain problems, there is a paradigm shift that can lead to the emergence of a new scientific discipline. This happens often through the creation of novel scientific collaborations. In this context, Becher & Trowler (2001) explained that, even if science proceeds toward more specific disciplines and thus researchers in different communities become less compatible, they are still incline to collaborate for mutual benefit. Herrera et al. (2010), Sun et al. (2013), Nowotny et al. (2013) suggested that the development of new topics is actually encouraged by the cross-fertilisation of established research areas and recognised that multidisciplinary approaches foster new developments and innovative thinking. Sun et al. (2013) and Osborne et al. (2014) provided empirical evidence to these theories by analysing the social dynamics of researchers and their effect on research communities and topics.

According to these theories, when a new scientific area emerges, it goes through two main phases. In the *initial stage* a group of scientists agree on some basic theories, build a conceptual framework and begin to establish a new scientific community. Afterwards, the area enters a *recognised phase* in which a substantial number of authors start working on it, producing and disseminating results (Couvalis 1997).

Inspired by previous theories, we hypothesize the existence of an even earlier phase, that we label *embryonic phase*, in which a topic has not yet been explicitly labelled or recognized by a research community, but exists as a fuzzy entity which entices a number of researchers from a variety of fields to converge and collaborate, with the aim of defining the mission and the paradigms of this potential research area.

We also hypothesize that it is possible to detect topics in this particular stage by analysing the *dynamics* of established topics. In this context, we define *dynamics* as all the significant trends regarding a topic or the interaction between topics or between entities linked to these topics, such as publications, authors, venues. For example, the sudden appearance of a number of publications concerning a combination of previously uncorrelated topics may suggest that some pioneer researchers are investigating new possibilities and maybe shaping a new emerging area. In the same way, as pointed out in Salatino (2015), we can hypothesize a wide array of relevant dynamics that could anticipate the creation of a new research area, such as a new collaboration between two or more research communities (see for example Osborne et al. (2014)), the creation of interdisciplinary workshops, a rise in the number of experts working on a certain combination of topics, a significant change in the vocabulary associated with relevant topics (Cano Basave et al. 2016), and so on.

This paper presents a study of some dynamics preceding the creation of novel topics which supports our hypothesis. In particular, we analysed the topic co-occurrence graphs and found that the emergence of novel research topics can be anticipated by a significant increase of the pace of collaboration and density in the co-occurrence graphs of related topics.

This study was performed in the 2000-2010 interval on a sample of three million publications. It was conducted by selecting sections of the co-occurrence graph where a new topic is about to emerge and analysing their interactions in the previous five years versus a control group of subgraphs associated to established topics. The analysis was performed with two different approaches that integrate statistics and semantics. It was found that the pace of collaboration and density measured in the sections of the network that will give rise to a new topic are significantly higher ($p < 0.0001$) than the one in the control group. These findings support our hypothesis about the existence of an embryonic phase, yield new empirical evidences to the aforementioned theories and confirm the strong benefits of an interdisciplinary environment. In addition, the identified dynamics could be used to build new automatic methods for suggesting the emergence of a research topic in a certain conceptual area, which could be complementary to the current methods for detecting research topics. Indeed, while these new methods may be unable to generate an accurate specification of the topic, they should however be able to detect its emergence at an earlier stage, since they would not require a minimum amount of publications directly associated with the topic.

The study presented in this paper is an extension of the one published in (Salatino & Motta 2016). The new contribution of this paper are: 1) a larger sample (75 debutant topics and 100 established ones), 2) a new technique for measuring the density of the topic graphs, 3) a more exhaustive statistical analysis, including the comparison of the different approaches, 4) a revised state of the art, and 5) a more comprehensive discussion of the findings.

The rest of the paper is organized as follows. We will first review the literature regarding the early detection of topics, pointing out the existing gaps. Then we will describe the experimental approach used for the study, present the results and discuss their implications. Finally, we will summarize the main conclusions and outline future directions of research.

RELATED WORK

Topic detection and tracking is a task that has drawn much attention in the last years and has been applied to a variety of scenarios, such as social networks (Cataldi et al. 2010; Mathioudakis & Koudas 2010), blogs (Gruhl et al. 2004; Oka et al. 2006), emails (Morinaga & Yamanishi 2004) and scientific literature (Bolelli et al. 2009; Decker et al. 2007; Erten et al. 2004; Lv et al. 2011; Osborne et al. 2014; Sun et al. 2016; Tseng et al. 2009).

The state of the art presents several works on research trend detection, which can be characterised either by the way they define a topic or the techniques they use to detect them (Salatino 2015). Blei et al. (2003) developed the well-known Latent Dirichlet Allocation (LDA), an unsupervised learning method to extract topics from a corpus, which models topics as a multinomial distribution over words. Since its introduction, LDA has been extended and adapted in several applications. For example, Blei & Lafferty (2006) introduced

the Correlated Topic Model using the logistic normal distribution instead of the Dirichlet one, to address the issue that LDA fails to model correlations between topics. Griffiths & Tenenbaum (2004) developed the *hierarchical LDA* where topics are grouped together in a hierarchy. Further extensions incorporate other kinds of research metadata. For example, Rosen-Zvi et al. (2004) presented the Author-Topic Model (ATM) which includes authorship information and then associates each topic to a multinomial distribution over words and each author to a multinomial distribution over topics. Bolelli et al. (2009) introduced the Segmented Author-Topic model which further extends ATM by adding the temporal ordering of documents to address the problem of topic evolution. In addition, Chang & Blei (2010) developed the *relational topic model* which combines LDA and the network structure of documents to model topics. Similarly, He et al. (2009) combined LDA and citation networks in order to address the problem of topic evolution. Their approach detects topics in independent subsets of a corpus and then leverages citations to connect topics in different time frames. In a similar way, Morinaga & Yamanishi (2004) employed a probabilistic model called Finite Mixture Model to represent the structure of topics and analyse the changes in time of the extracted components to track emerging topics. However, this was evaluated on an email corpus, thus it is not clear how it would perform on scientific corpus. A general issue affecting this kind of approaches is that is not always easy to associate specific research areas to the resulting topic models.

In addition to LDA, the Natural Language Processing (NLP) community have also proposed a variety of tools for identifying topics. For example, Chavalarias & Cointet (2013) used CorText Manager to extract a list of 2000 n-grams representing the most salient terms from a corpus and derived a co-occurrence matrix on which they perform clustering analysis to discover patterns in the evolution of science. Jo et al. (2007) developed an approach that correlates the distribution of terms extracted from the text with the distribution of the citation graph related to publications containing those terms. Their work is based on the assumption that if a term is relevant to a particular topic, documents containing that term will have a stronger connection than randomly selected ones. However, this approach is not suitable for topics in their very early stage since it takes time for the citation network of a term to become tightly connected.

Duvvuru et al. (2013) analysed the co-occurring network of keywords in a scholarly corpus and monitored the evolution in time of the link weights for detecting research trends and emerging research areas. However, as Osborne & Motta (2012) pointed out, keywords tend to be noisy and do not always represent research topics – in many cases different keywords even refer to the same topic. For example, Osborne et al. (2014) showed that the use of a semantic characterisation of research topics yields better results for the detection of research communities. To cope with this problem, some approaches rely on taxonomies of topics. For example, Decker et al. (2007) matched a corpus of research papers to a taxonomy of topics based on the most significant words found in titles and abstracts, and analysed the changes in the number of publications associated with topics. Similarly, Erten et al. (2004) adopted the ACM Digital Library taxonomy for analysing the evolution of topic graphs and monitoring research trends. However, human crafted taxonomy tend to evolve slowly and in a fast-

changing research field such as *Computer Science* (Pham et al. 2011) it is important to rely on constantly updated taxonomies. For this reason, in our experiment we adopted an ontology of Computer Science automatically generated and regularly updated by the Klink-2 algorithm developed by Osborne & Motta (2015).

In brief, the state of the art provides a wide collection of approaches for detecting research trends. However, these focus on already recognised topics, associated with either a label or, in the case of probabilistic topics models, with a set of terms that should have previously appeared in a good number of publications. Therefore, detecting research trends at a very early stage is still an open challenge.

MATERIALS AND METHODS

The aim of this study was to measure the association between the emergence of a new topic and the increase of pace of collaboration and density previously observed in the co-occurrence graphs of related topics. To this end, we represent topics and their relationships in a certain time frame as a graph in which nodes are topics whereas edges represent their co-occurrences in a sample of publications. This is a common representation for investigating topic dynamics (Boyack et al. 2005; Leydesdorff 2007; Newman 2001) and we will refer to it as *topic graph* or *topic network* in the following. To pursue our analysis, we analysed 75 topics that debuted in the 2000-2010 period using 100 established topics as a control group.

In our previous work (Salatino & Motta 2016), we conducted a similar analysis on a smaller sample. The sample analysed in this paper was selected by iteratively adding new topics until we reached data saturation (Fusch & Ness 2015), i.e. the results of the analysis did not vary significantly with the inclusion of new data points.

In the following sections we will describe the dataset, the semantically enhanced topic graph and the methods used to measure the pace of collaboration and the density of the subgraphs.

The raw data and the outcomes of this study are available at http://technologies.kmi.open.ac.uk/rexplore/peerj2016/.

Semantic Enhanced Topic Network

We use as dataset the metadata describing 3 million papers in the field of *Computer Science* from a dump of the well-known Scopus dataset[1]. In this dataset each paper is associated to a number of keywords that could be used to build the topic graph. However, as pointed out in (Osborne & Motta 2012), the use of keywords as proxies for topics suffers from a number of problems: some keywords do not represent topics (e.g., *case study*) and multiple keywords can refer to the same topic (e.g., *ontology mapping* and *ontology matching*).

The literature offers a number of methods for characterizing research topics. Probabilistic topic models, such as LDA, are very popular solutions, which however are most effective in scenarios where fuzzy classification is acceptable, there is no good domain knowledge, and it

[1] https://www.elsevier.com/solutions/scopus

is not important for users to understand the rationale of a classification. However, these tenets do not apply to this study. Furthermore, it is not easy to label the topics produced by a probabilistic topic model with specific and distinct research areas. Conversely, in this study is important to be able to associate topics with well-established research areas.

A second approach, used by a number of digital libraries and publishers is tagging publications with categories from a pre-determined taxonomy of topic. Some examples include the ACM computing classification system[2], the Springer Nature classification[3], Scopus subject areas[4], and the Microsoft Academic Search classification[5]. This solution has the advantage of producing sound topics, agreed upon by a committee of experts. However, these taxonomies suffer from some common issues. First, building a large taxonomy requires a large number of experts; it is an expensive and lengthy process. Hence, they are seldom updated and grow obsolete very quickly. For example, the 2012 version of the ACM classification was finalized fourteen years after the previous version. In addition, these taxonomies are very coarse-grained and usually contain general fields rather than fine-grained research topics.

We address these issues by characterizing our topics according to the Klink-2 ontology of Computer Science, which describes the relationships between more than 15,000 research areas. Klink-2 is an algorithm which is able to generate very granular ontologies and update them regularly by analysing keywords and their relationships with research papers, authors, venues, and organizations and by taking advantage of multiple knowledge sources available on the web. Klink-2 is currently integrated in the Rexplore system (Osborne et al. 2013), a modern tool for exploring and making sense of scholarly data, which provides semantic-aware analytics. Klink-2 was run on a set of 35,983 keywords from a corpus of 16 million publications in the field of Computer Science, producing an ontology that contains 15,961 terms, after filtering out 20,022 keywords that did not represent topics, were unrelated to any other topic in the taxonomy or were associated with a low number of publications (Osborne & Motta 2015).

We took advantage of the Klink-2 ontology by filtering from our dataset the keywords that do not represent specific research areas and aggregating keywords representing the same concept, i.e., linked by a *relatedEquivalent* relationship in the ontology (Osborne et al. 2013). For example, we aggregated keywords such as “semantic web”, “semantic web technology” and “semantic web technologies” in a single semantic topic and assigned it to all publications associated with these keywords.

We used the resulting semantic topics to build sixteen topic networks representing the topic co-occurrences in the 1995-2010 timeframe. Each network is a fully weighted graph $G_{year} = (V_{year}, E_{year})$, in which V is the set of topics while E is the set of links representing the topic

[2] http://www.acm.org/publications/class-2012
[3] http://www.nature.com/subjects
[4] https://www.elsevier.com/solutions/scopus/content
[5] http://academic.research.microsoft.com/

co-occurrences. The node weight represents the number of publications in which the topic appears in a certain year, while the link weight is equal to the number of publications in which two topics co-occur together in the same year.

Graph Selection

We randomly selected 75 topics that debuted in the period between 2000 and 2010 as treatment group (also referred as debutant group). A topic debuts in the year in which its label first appears in a research paper. The control group (also referred as non-debutant group), was obtained by selecting 100 well-established topics. We considered a topic as well-establish if: i) it debuted before 2000, ii) it appears in the Klink Ontology, iii) it is associated each year with a substantial and consistent number of publications. As an example, Figure 1 shows the evolution through time of the well-established topic *Software Agents* in terms of number of active authors and papers published about it. The figure shows that the topic made its debut in 1993 and in the year 2000 reached a rate of over 500 publications per year and more than 1500 authors working on it. We can thus consider it established in the context of our study.

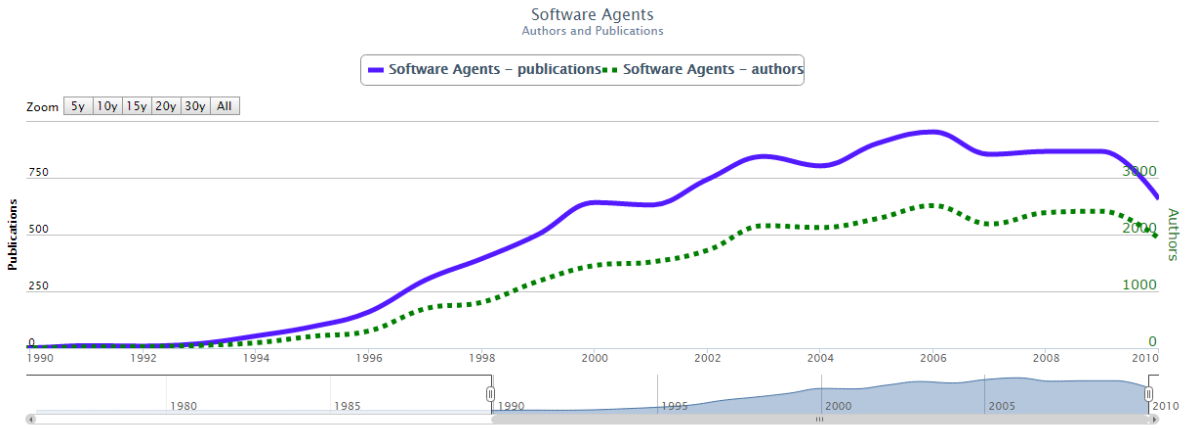


Figure 1. Evolution of the topic Software Agents in terms of number of authors and number of publications per year. The chart has been produced by the Rexplore system.

We assume that a new topic will continue to collaborate with the topics that contributed to its creation for a certain time after its debut. This assumption was discussed and tested in previous work (Osborne & Motta 2012) where it was used for finding historical subsumption links between research areas. Hence, as summarized by Figure 2, for each debuting topic we extracted the portion of topic network containing its *n* most co-occurring topics from the year of debut until nowadays and analysed their activity in the five years preceding its year of debut. Since we want to analyse how the dimension of these subgraphs could influence the results, we tested different values of *n* (20, 40, and 60). For example, if a topic *A* made its debut in 2003, the portion of network containing its most co-occurring topics will be analysed in the 1998-2002 timeframe. We repeated the same procedure on the topics in the control group, assigning them a random year of analysis within the decade 2000-2010. In the previous study (Salatino & Motta 2016), we selected 50 established topics and we assigned a random *year of analysis* to each of them. For this study, we randomly assigned each established topic to two consecutive years within the decade 2000-2010, with the

consequence of doubling the control group and thus reducing the noise and smoothing the resulting measures.

In brief, the selection phase associates to each topic from the treatment and the control groups (also referred as *testing topics* or *topics under test*) a graph G^{topic} :

$$G^{topic} = G^{topic}_{year-5} \cup G^{topic}_{year-4} \cup G^{topic}_{year-3} \cup G^{topic}_{year-2} \cup G^{topic}_{year-1} \quad (1)$$

which corresponds to the collaboration network of a debutant topic in the five years prior to its emergence (or year of analysis for non-debutant topics). In particular, each year corresponds to the sub-graphs G^{topic}_{year-i}:

$$G^{topic}_{year-i} = (V^{topic}_{year-i}, E^{topic}_{year-i}) \quad (2)$$

in which V^{topic}_{year-i} is the set of most co-occurring topics in a particular year and E^{topic}_{year-i} is the set of edges that link nodes in the set V^{topic}_{year-i}.

The graphs associated to the debutant topics included 1,357 unique topics, while the ones associated to the control group included 1,060 topics.

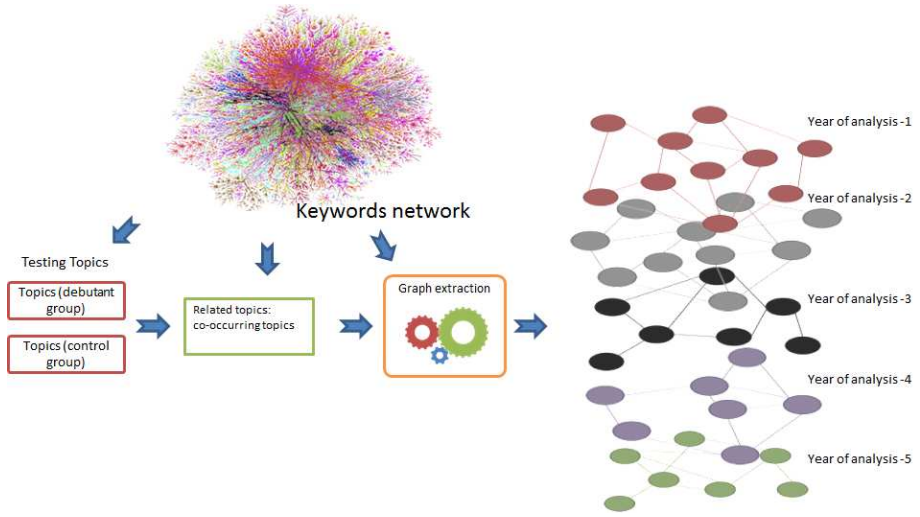


Figure 2: Workflow representing all the steps for the selection phase.

Graph Analysis

We assess the dynamics in the graphs with two main approaches: cliques-based and triad-based. The first transforms the graph in 3-cliques, associates to each of them a measure reflecting the increase in collaboration between the relevant topics and then averages the results over all 3-cliques. The second measures the increase in the topics graph density using the triad census technique (Davis & Leinhardt 1967). In the following two sections we will describe both methods in details.

Cliques-based method

This approach is based on the intuition that we can measure the collaboration pace of a graph by analysing the diachronic activity of triangles of collaborating topics. To this end, we first extracted all 3-cliques from the five sub-graphs associated to each topic under analysis. A 3-clique, as shown in Figure 3, is a complete sub-graph of order three in which all nodes are connected to one another and is employed for modelling small groups of entities close to each other (Luce & Perry 1949).

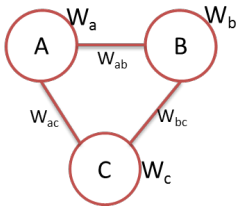


Figure 3. An instance of a 3-clique containing nodes and links weights.

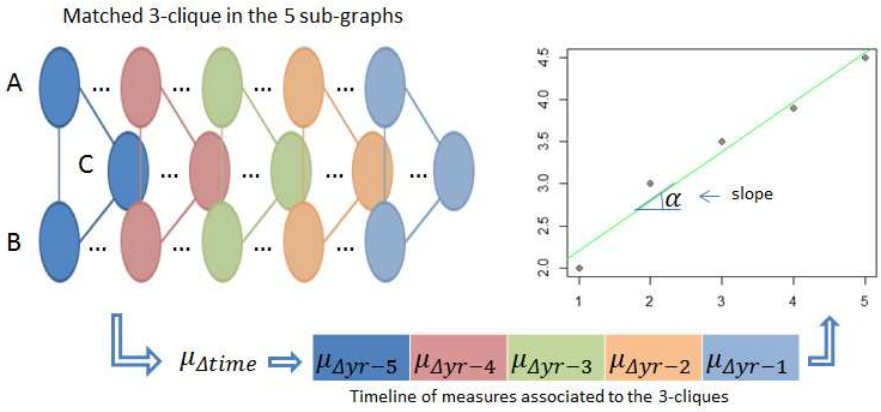


Figure 4. Main steps of the analysis phase.

To study the dynamics preceding the debut of each topic, we analysed the evolution of the same 3-clique in subsequent years. Figure 4 summarizes the process. Considering a 3-clique having nodes $\{A, B, C\}$, we quantify its collaboration index μ_Δ in a certain year by taking into account both node weights $\{W_a, W_b, W_c\}$ and link weights $\{W_{ab}, W_{bc}, W_{ca}\}$.

$$\begin{aligned} \mu_{A-B} &= harmmean\big(P(A \mid B), P(B \mid A)\big) \\ \mu_{B-C} &= harmmean\big(P(B \mid C), P(C, B)\big) \\ \mu_{C-A} &= harmmean\big(P(C \mid A), P(A \mid C)\big) \\ \mu_\Delta &= harmmean\big(\mu_{A-B}, \mu_{B-C}, \mu_{C-A}\big) \end{aligned} \quad (3)$$

The index μ_Δ is computed by mean of Equation 3. The strength of collaboration μ_{x-y} between two nodes of the topic network, x and y, is computed as the harmonic mean of the conditional probabilities $P(y|x)$ and $P(x|y)$, where $P(x|y)$ is the probability that a publication associated with a topic x will be associated also with a topic y in a certain year. The advantage of using conditional probabilities over the number of co-occurrences is that

the resulting value μ_{x-y} is already normalised according to the number of publications associated to each topic. Finally, μ_{Δ} is computed as the harmonic mean of the strength of collaboration of the three links of a 3-clique. This solution was adopted after testing alternative approaches during the *preliminary evaluation*, as will be discussed in the Findings section.

The evolution of the 3-clique collaboration pace can be represented as a timeline of values in which each year is associated with its collaboration pace, as in Equation 4. We assess the increase of the collaboration pace in the period under analysis by computing the slope of the linear regression of these values.

$$\mu_{\Delta\text{time}}^{clique-i} = [\mu_{\Delta\text{yr}-5}, \mu_{\Delta\text{yr}-4}, \mu_{\Delta\text{yr}-3}, \mu_{\Delta\text{yr}-2}, \mu_{\Delta\text{yr}-1}] \quad (4)$$

Initially, we tried to determine the trend of a clique by simply taking the difference between the first and last values of the timeline ($\mu_{\Delta yr-5} - \mu_{\Delta yr-1}$). However, this method ignores the other values in the timeline and can thus neglect important information. For this reason, we applied instead the linear interpolation method on the five measures using the least-squares approximation to determine the linear regression of the time series $f(x) = a \cdot x + b$. The slope *a* is then used to assess the increase of collaboration in a clique. When *a* is positive the degree of collaboration between the topics in the clique is increasing over time, while when is negative the number and intensity of collaborations are decreasing.

Finally, the collaboration pace of each sub-graph was measured by computing the mean of all slopes associated with the 3-cliques.

To summarize, for each testing topic we selected a subgraph of related topics in the five years preceding the year of debut (or *analysis* for topics in the control group). We then extracted the 3-cliques and associated each of them with a vector representing the evolution of their pace of collaboration. The trend of each clique was computed as the angular coefficient of the linear regression of these values. Finally, the increase in the pace of collaboration of a subgraph was obtained by averaging these values.

Triad-based method

The triad-based method employs the triad census (Davis & Leinhardt 1967) to measure the change of topology and the increasing density of the subgraphs during the five year period. The triad census of an undirected graph, also referred as global 3-profiles, is a four dimensional vector representing the frequencies of the four isomorphism classes of triad, as shown in Figure 5.

The triad census summarises the structural information in networks and is useful to analyse structural properties in social networks. In has been applied to several scenarios, such as identifying spam (Kamaliha et al. 2008; O'Callaghan et al. 2012), comparing networks (Pržulj 2007), analysing social networks (Faust 2010; Ugander et al. 2013) and so on.

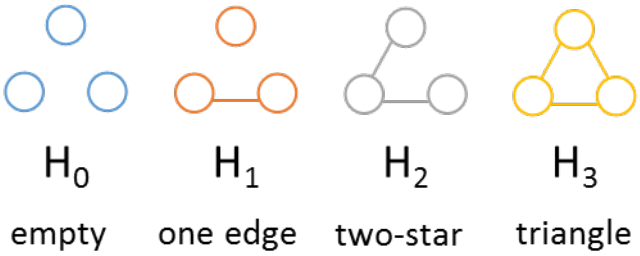


Figure 5. The four isomorphism classes of triad. The triad census consists in counting the frequencies of *Hi* of the input graph.

In this study, we used triad census to describe all the sub-graphs G^{topic}_{year-i} associated to a particular testing topic in terms of frequencies of H_i (see Figure 5) and then evaluate how the frequencies of *empties* (H_0), *one edges* (H_1), *two-starts* (H_2) and *triangles* (H_3) changed in time. Figure 5 illustrates the four classes of triads for an undirected graph as in the case of topic network. Naturally an increase of the numbers of triangles suggests the appearance of a number of new collaborations clusters between previous distant topics.

Differently from the previous approach, the triad census does not consider the weight of links, but only their existence. Hence, it is useful to assess how including links with different strength affects the analysis. To this end, we performed three experiments in which we considered only links associated with more than 3, 10 and 20 topic co-occurrences.

Figure 6 shows the workflow for analysing the evolution of topology of networks related to a testing topic, in the five years preceding its debut.

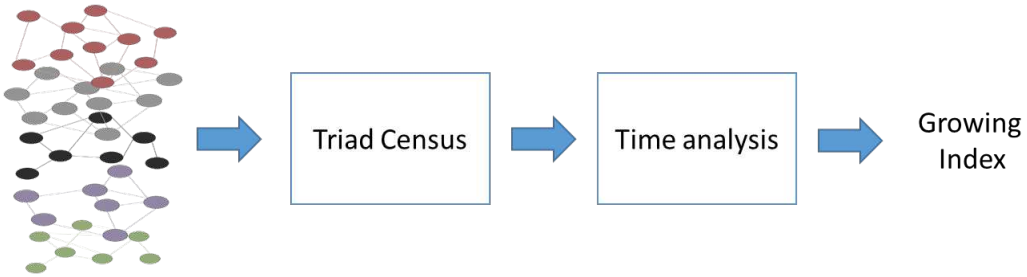


Figure 6. Main step of the analysis phase for the triad census approach.

We first performed the triad census over the five graphs associated to each testing topic. For example, Table 1 shows the results of the triad census over the five sub-graphs associated to the debutant topic *Artificial Bee Colonies*.

Table 1. Frequencies of H_i obtained performing triad census on the debutant topic "Artificial Bee Colonies"

Graph	H_0	H_1	H_2	H_3
G^{topic}_{year-5}	446	790	807	882
G^{topic}_{year-4}	443	854	915	1064
G^{topic}_{year-3}	125	486	967	1698

G_{year-2}^{topic}	100	410	908	1858
G_{year-1}^{topic}	68	486	849	2251

377

378 We then measured whether the collaboration graph was becoming denser by analysing the
379 change of frequencies associated with H_i (see Figure 7). To do so, we computed the
380 percentage growth of each H_i using Equation 5.

$$\%GrowthH_i = \frac{(H_i^{Yr-1} - H_i^{Yr-5}) * 100}{H_i^{Yr-5}} \quad (5)$$

381

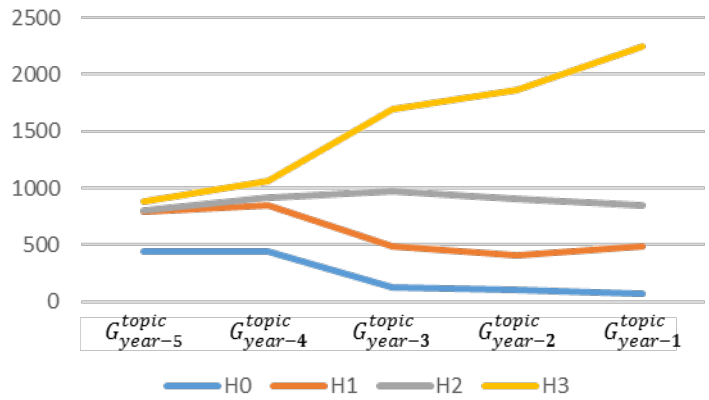
382 Then, we used Equation 6, which performs a weighted summation of all the contributions of
383 percentage of growth.

384

$$GrowingIndex_{topic} = \sum_{i=0}^{3} i \cdot \%GrowthH_i \quad (6)$$

385 The *growth index* takes into account all the isomorphism classes, even if the number of
386 triangles (H_3) can by itself be a fair indicator of the density. Indeed, previous studies by Faust
387 (2010) and Holland & Leinhardt (1976) showed that all four classes of triads are useful for
388 computing useful properties of the network, including transitivity, intransitivity and density.
389 In our case, taking in consideration only H_3 might fail to detect some subtler cases,
390 characterized for example by a significant increase of H_2 and decrease of H_1 and H_0.

391



392

393 Figure 7: Development in time of the frequencies of H_i in the network related to the emergence of "Artificial Bee Colonies".

394 To summarize, the triad-based method received the same input of the clique-based method.
395 For each of these five subgraphs associated to a topic, we performed the triad census
396 obtaining the different frequencies H_i in different years. We then analysed them
397 diachronically to quantify the increase in density.

398

RESULTS

In this section we report the results obtained by analysing the debutant and the control groups with the previously discussed methods. We will describe:

- The preliminary evaluation performed on a reduced dataset for assessing the metrics used in the Cliques-based method;
- The full study using the Cliques-based method;
- The full study using the Triads-based method.

Preliminary evaluation with alternative cliques-based methods

We initially conducted a preliminary evaluation with the aim of choosing the most effective Cliques-based method for assessing the pace of collaboration. This test focused on the subgraph of the 20 most co-occurring topics associated to the topic Semantic Web (debuting in 2001) and Cloud Computing (2006) versus a control group of 20 subgraphs associated to a non-debutant group. We tested on this dataset two techniques to compute the weight of a clique (i.e., harmonic mean and arithmetic mean) and two methods to evaluate its trend (i.e., computing the difference between the first and the last values and linear interpolation). Hence, we evaluated the following four approaches:

- **AM-N**, which uses the arithmetic mean and the difference between first and last value;
- **AM-CF**, which uses the arithmetic mean and the linear interpolation;
- **HM-N**, which uses the harmonic mean and the difference between first and last value;
- **HM-CF**, which uses the harmonic mean and the linear interpolation.

Figure 8 illustrates the average pace of collaboration for the sub-graphs associated to each topics according to these methods (thick horizontal black lines) and the range of their values (thin vertical line). The results support the initial hypothesis: according to all methods, the pace of collaboration of the cliques within the portion of network associated with the emergence of new topics is positive and higher than the ones of the control group. Interestingly, the pace of collaboration of the control group is also slightly positive. Further analysis revealed that this behaviour is probably caused by the fact that the topic network becomes denser and noisier in time. Figure 9 confirms this intuition illustrating the fast growth of the number of publications per year in the dataset during the time window 1970-2013.

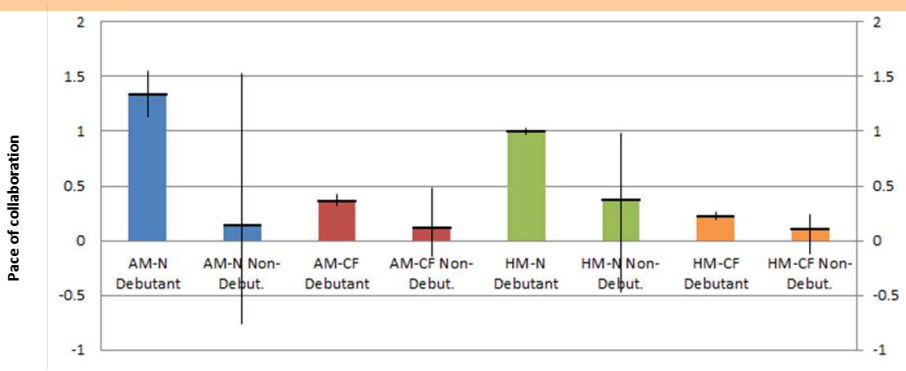


Figure 8. Overall directions of the sub-graphs related to testing topics in both debutant and control group with all the four approaches.

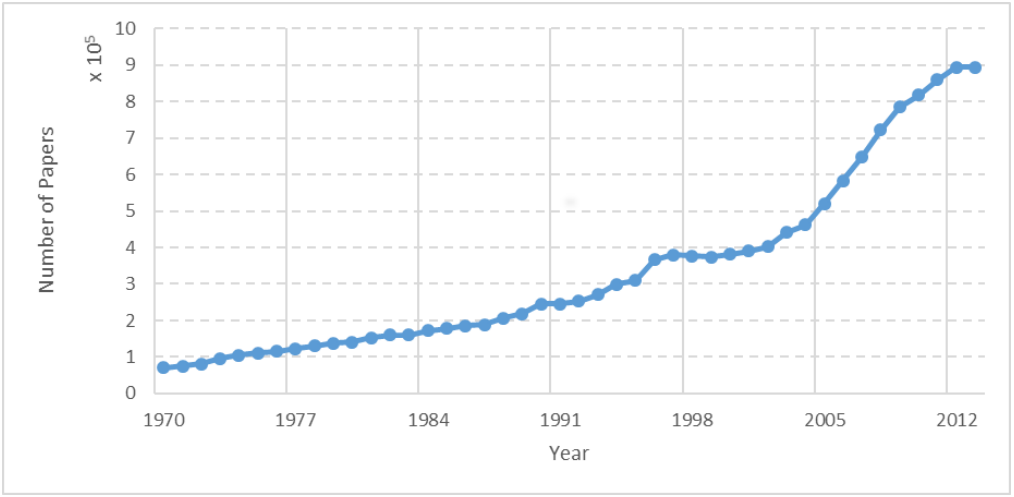


Figure 9. Number of papers each year in period 1970-2013

The approaches based on the simple difference (AM-N and HM-N) exhibit the larger gaps between the two groups in terms of the average pace of collaboration. However, the ranges of values actually overlap, making it harder to assess if a certain sub-group is incubating a novel topic. The same applies to AM-CF. HM-CF performs better and even if the values slightly overlap when averaging the pace over different years they do not when considering single years. Indeed, analysing the two ranges separately in 2001 and 2006 (see Figure 10), we can see that the overall collaboration paces of the debutant topics (DB) are always significantly higher than the control group (NDB).

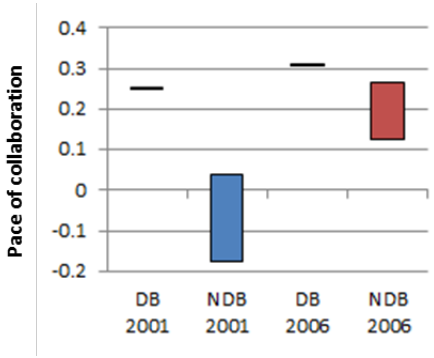


Figure 10. Overall directions of the sub-graphs related to testing topics in both debutant and control group in HM-CF approach

We ran the Student's t-test on the sample of data provided by the HM-CF approach, to verify whether the two groups belong to different populations. The test yielded $p < 0.0001$, which allowed us to reject the null hypothesis that the differences between the two distributions were due to random variations[6]. On the basis of this result, we could further confirm that the HM-CF approach performs better compared to the other approaches. For this reason, we selected the combination of the *harmonic mean* and the *linear interpolation* as the approach for the full study using the clique-based method.

The results of HM-CF show also interesting insights on the creation of some well-known research topics. Table 2 and Table 3 list the cliques which exhibited a steeper slope for semantic web and cloud computing. We can see that *Semantic Web* was anticipated in the 1996-2001 timeframe by a significant increase in the collaborations of the *World Wide Web* area with topics such as *Information Retrieval*, *Artificial Intelligence*, and *Knowledge Based Systems*. This is consistent with the initial vision of the semantic web, defined in the 2001 by the seminal work of Tim Berners-Lee (Berners-Lee et al. 2001). Similarly, *Cloud Computing* was anticipated by an increase in the collaboration between topics such as *Grid Computing*, *Web Services*, *Distributed Computer Systems* and *Internet*. This suggests that our approach can be used both for forecasting the emergence of new topics in distinct subsections of the topic network and for identifying the topics that gave rise to a research area.

Table 2. Ranking of the cliques with highest slope value for the "semantic web".

Topic 1	Topic 2	Topic 3	Slope
world wide web	information retrieval	search engines	2.529
world wide web	user interfaces	artificial intelligence	1.12
world wide web	artificial intelligence	knowledge representation	0.974
world wide web	knowledge based systems	artificial intelligence	0.850
world wide web	information retrieval	knowledge representation	0.803

Table 3. Ranking of the cliques with highest slope value for the "cloud computing".

Topic 1	Topic 2	Topic 3	Slope
grid computing	distributed computer systems	web services	1.208
web services	information management	information technology	1.094
grid computing	distributed computer systems	quality of service	1.036
internet	quality of service	web services	0.951
web services	distributed computer systems	information management	0.949

Cliques-based method study

We applied the cliques-based methods on the subgraphs associated to both topics in the treatment and control groups. Figure 11 reports the results obtained by using subgraphs composed by the most 20, 40 and 60 co-occurring topics. Each bar shows the mean value of the average pace of collaboration for the debutant (DB) and non-debutant (NDB) topics. As

[6] $p < 0.0001$ is the conventional statistical representation to indicate an extremely high statistical significance (> 500 times stronger than the conventional 0.05 threshold for claiming significance). It includes all mathematical outcomes from 0 to below 0.0001, which are essentially equivalent in assessing the excellent significance.

before, the average pace computed in the portion of topic network related to debutant topics is higher than the one of the control group.

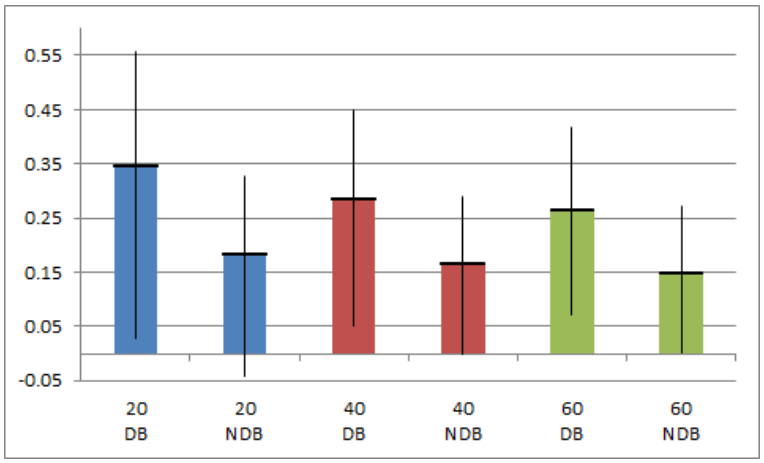


Figure 11. Average collaboration pace of the sub-graphs associated to the treatment (DB) and control group (NDB), when selecting the 20, 40 and 60 most co-occurring topics. The thin vertical lines represent the ranges of values.

Since the pace of collaboration changes significantly according to the period considered, it is useful to study it across different years. Figure 12, Figure 13 and Figure 14, show the average collaboration pace for each year when considering the 20, 40 and 60 most co-occurring topics. In all cases the collaboration pace for the debutant topics is higher than the one for the control group. We can also notice that in the last five years the overall pace of collaboration for both debutant and non-debutant topics suffered a significant fall. This is due to the fact that the topic network became denser and noisier in recent years.

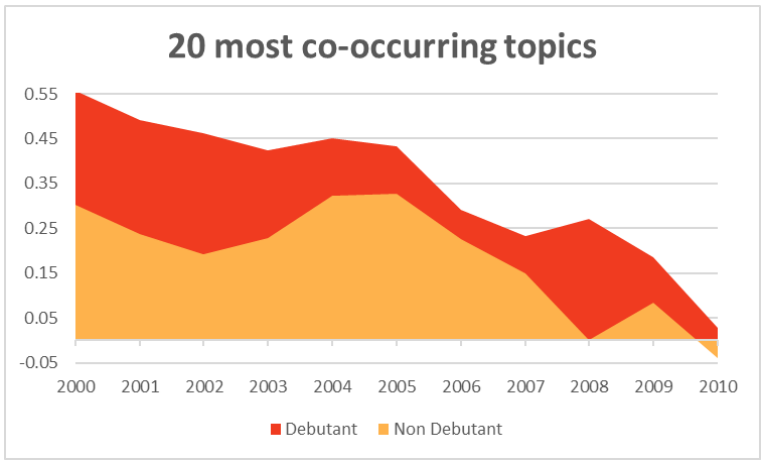


Figure 12. Average collaboration pace per year of the sub-graphs related to testing topics in both debutant and control group considering their 20 most co-occurring topics. The year refers to the year of analysis of each topic.

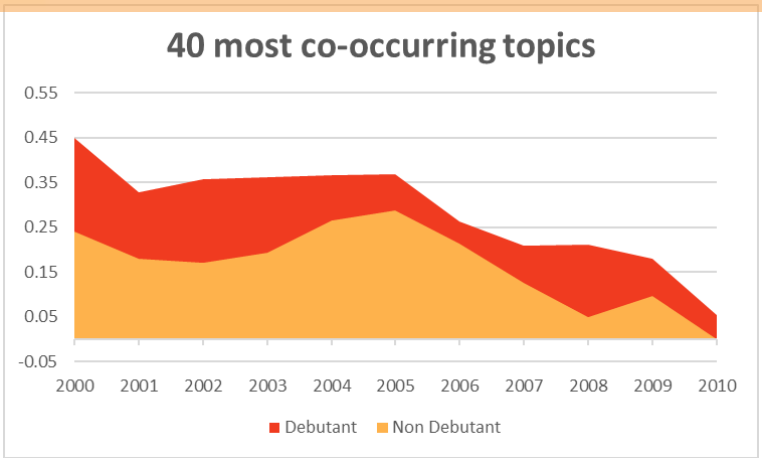


Figure 13. Average collaboration pace per year of the sub-graphs related to testing topics in both debutant and control group considering their 40 most co-occurring topics. The year refers to the year of analysis of each topic.

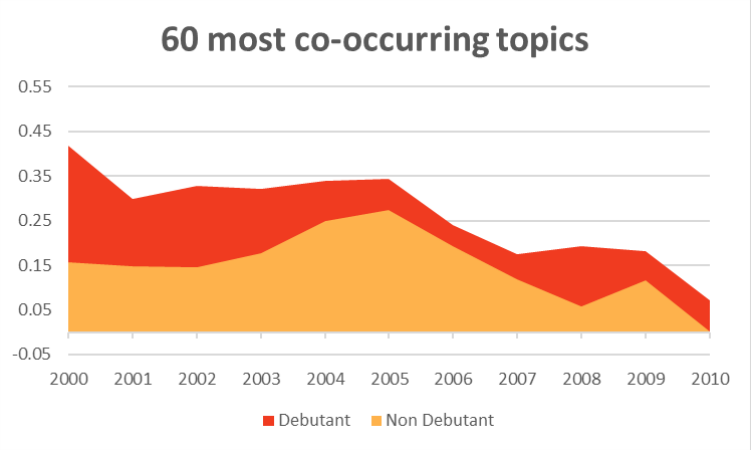


Figure 14. Average collaboration pace per year of the sub-graphs related to testing topics in both debutant and control group considering their 60 most co-occurring topics. The year refers to the year of analysis of each topic.

Table 4 shows as example a number of debutant topics and their collaboration pace versus the collaboration pace of the control group in the same year. We can see how the appearance of a good number of well-known topics that emerged in the last decade was actually anticipated by the dynamics of the topic network.

We ran the Student's t-test on the groups in different years, in order to confirm that the two distributions belong to different populations. In all cases it yielded $p < 0.0001$ in all years. However, the experiment containing 60 most co-occurring topics allows to better discriminate debutant topics from non-debutant ones. Indeed, the p-values obtained by this solution are lower than the one yielded by the other two experiments for every single year of the period under analysis.

In conclusion, the results confirm that the portions of the topic network in which a novel topic will appear exhibit a measurable fingerprint, in terms of increased collaboration pace, well before the topic is recognized and labelled by researchers.

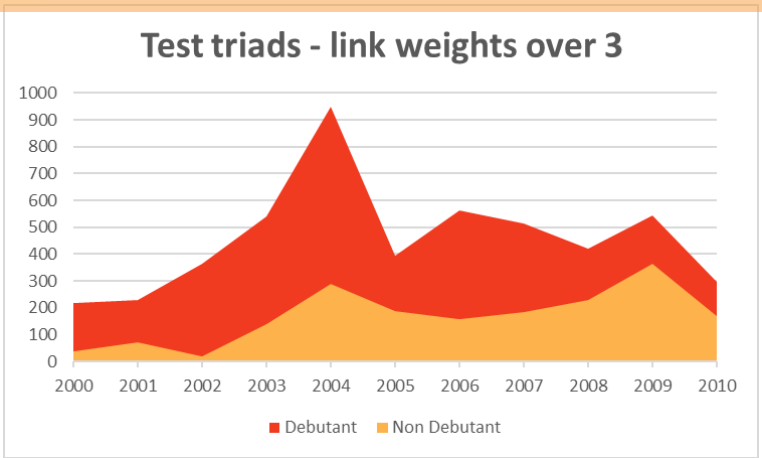
Table 4. Collaboration pace of the sub-graphs associated to selected debutant topics versus the average collaboration pace of the control group in the same year of debut.

Topic	Collaboration Pace	Standard Collaboration pace
service discovery (2000)	0.455	0.156
ontology engineering (2000)	0.435	0.156
ontology alignment (2005)	0.386	0.273
service-oriented architecture (2003)	0.360	0.177
smart power grids (2005)	0.358	0.273
sentiment analysis (2005)	0.349	0.273
semantic web services (2003)	0.349	0.177
linked data (2004)	0.348	0.250
semantic web technology (2001)	0.343	0.147
vehicular ad hoc networks (2004)	0.342	0.250
mobile ad-hoc networks (2001)	0.342	0.147
p2p network (2002)	0.340	0.145
location based services (2001)	0.331	0.147
service oriented computing (2003)	0.331	0.177
ambient intelligence (2002)	0.289	0.145
social tagging (2006)	0.263	0.192
wireless sensor network (2001)	0.258	0.147
community detection (2006)	0.243	0.192
cloud computing (2006)	0.241	0.192
user-generated content (2006)	0.240	0.192
information retrieval technology (2008)	0.231	0.057
web 2.0 (2006)	0.224	0.192
ambient assisted living (2006)	0.224	0.192
Internet of things (2009)	0.221	0.116

Triads-based method study

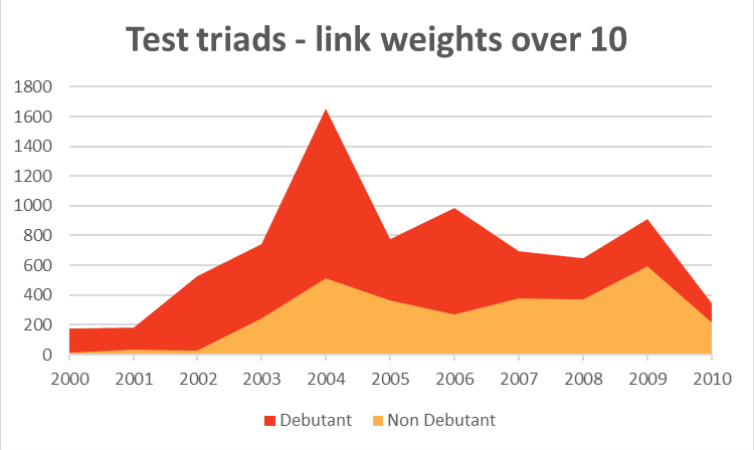
We applied the triads-based methods on the subgraphs composed by the 60 most co-occurring topics, since this configuration provided the best outcomes in previous tests. We performed multiple tests by filtering links associated with less than 3, 10 and 20 co-occurrences, for understanding how the collaboration strength influences the outcome.

Figure 15 reports the average value of the growing indexes when discarding links with less than 3 co-occurrences. The approach allows to discriminate well the portion of networks related to debutant topics from the ones related to the control group and the collaboration pace associated with the debutant topics is always higher than its counterpart. Figure 16 and Figure 17 report the results obtained by removing links with less than 10 and 20 co-occurrences. The gap between the groups in these two last experiments is reduced in comparison with the first experiment. This suggest that considering weak connections is more beneficial for discriminating the two groups. Nonetheless, the indexes associated with debutant topics are always higher than the ones associated to non-debutant ones. The 2004 peak is caused by the debut of number of topics associated with particularly strong underlying dynamics, such as *Linked Data*, *Pairing-based Cryptography*, *Microgrid* and *Privacy Preservation*.



531

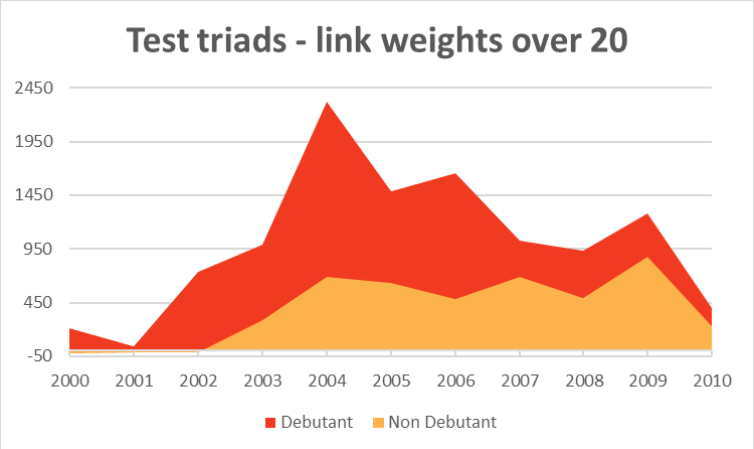
532 Figure 15. Average growing index per year of the sub-graphs related to the topics in both debutant and non-debutant group
533 considering their 60 most co-occurring topics and filtering links associated with less than 3 publications.



534

535 Figure 16. Average growing index per year of the sub-graphs related to the topics in both debutant and non-debutant group
536 considering their 60 most co-occurring topics and filtering links associated with less than 10 publications.

537



538

539 Figure 17. Average growing index per year of the sub-graphs related to the topics in both debutant and non-debutant group
540 considering their 60 most co-occurring topics and filtering links associated with less than 20 publications.

541 Table 5 reports as an example the triad census performed over the subgraph associated to the
542 topic *Semantic Web Technologies* (SWT) debuting in the 2001. We can see an increase in the

number of triangles (H_3) and two-stars (H_2), mirroring the increasing density of the topic network. Again, this phenomenon is more evident when using also weak links (< 3). The percentage of growth of full triangles is 109% in the first test and then it decreases to 86% (< 10) and 36 % (< 20).

Table 5. The results of the triad census performed on the network associated with the debutant topic "semantic web technology" removing links associated with less than 3 (left), 10 (right) and 20 (bottom) publications.

Removing links < 3

Graph	H_0	H_2	H_2	H_3
1996	1124	1157	658	337
1997	928	1237	670	441
1998	1255	1353	657	389
1999	1307	1431	861	461
2000	913	1399	1043	705

Removing links < 10

H_0	H_2	H_2	H_3
641	676	316	138
1022	828	315	135
585	705	300	181
1222	1098	413	192
1482	1361	554	257

Removing links < 20

Graph	H_0	H_2	H_2	H_3
1996	796	509	174	61
1997	632	432	204	62
1998	525	418	145	52
1999	569	497	187	77
2000	842	618	228	83

Table 6 shows a selection of debutant topics and their growing index compared with the growing index of the control group in the same year. We can compare this table to Table 4 to appreciate how the two methods used in this study reflect the same behaviour.

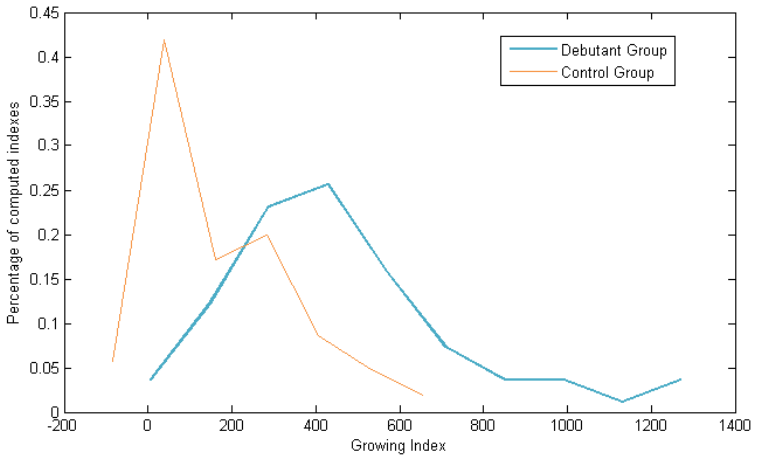


Figure 18. Distributions of growing indexes for both groups when filtering links associated with less than 3 publications.

As before, we ran Student's t-test over the two distributions of growing indexes, for all the three experiments. It yielded $p < 0.0001$ for all the experiments. Figure 18 shows as an example the distribution obtained in the first test.

Hence, also the results of this second experiment confirm our initial hypothesis. In addition, if we use the p-values for measuring the relative distance between the sample means, the technique which include weaker links performs better in discriminating the two populations.

Table 6. Growing indexes of sub-graphs associated to selected debutant topics versus the average growing index of the control group in the same year of debut.

Topic	Growing Index	Standard Growing Index
service discovery (2000)	290.29	35.97
ontology engineering (2000)	207.22	35.97
ontology alignment (2005)	399.60	186.89
service-oriented architecture (2003)	628.07	140.17
smart power grids (2005)	637.53	186.89
sentiment analysis (2005)	354.10	186.89
semantic web services (2003)	439.85	140.17
linked data (2004)	590.81	289.94
semantic web technology (2001)	465.53	72.71
vehicular ad hoc networks (2004)	859.44	289.94
mobile ad-hoc networks (2001)	87.31	72.71
p2p network (2002)	305.28	18.92
location based services (2001)	595.90	72.71
service oriented computing (2003)	422.92	140.17
ambient intelligence (2002)	308.34	18.92
social tagging (2006)	429.77	157.69
community detection (2006)	583.21	157.69
cloud computing (2006)	695.79	157.69
user-generated content (2006)	485.89	157.69
information retrieval technology (2008)	552.14	227.02
web 2.0 (2006)	387.42	157.69
ambient assisted living (2006)	940.79	157.69
Internet of things (2009)	580.33	167.86

DISCUSSION

In this study, we analysed the topic network with the aim of confirming the hypothesis that the emergence of new research areas is anticipated by the interaction of already existing topics. We examined the pace of collaboration (via the cliques-based method) and the change in topology (via the triads-based method) in portions of network related to debutant topics, showing that is possible to effectively discriminate areas of the topic graph associated to the future emergence of new topics. In particular, the first experiments showed that the subgraphs associated with the emergence of a new topic exhibit a significant higher pace of collaboration than the control group of subgraphs associated with established topics ($p < 0.0001$). Similarly, the second experiment showed that the graphs associated with a new topic display a significant higher increase in their density than the control group ($p < 0.0001$). We can thus confirm that these two dynamics can play a key role when performing the detection of embryonic topics.

However, the ability of these two approaches in discriminating the debutant graph from the control group varies according to the period. Looking at the best results, reported in Figure 14 and Figure 15, it appears that the cliques-based approach works better (according to the resulting p-values) in the first years of the decade (2000-2004) while the triads-based approach performs in the last years (2005-2010). This may indicate that the second approach

works better when the topic network is nosier and denser, as it is in the second period. In this sense, the two approaches are complementary and the choice of the best one will depend on the characteristics of the topic graph under analysis. We plan to study other dynamics, regarding authors, venues, citations and so on, with the aim of further understanding the patterns that precede the emergence of research topic.

The results of this study should allow us to develop new methods for detecting the aforementioned dynamics in specific sections of the topics graph and suggesting that a new research area may emerge from a combination of other topics. Indeed, even simply using a threshold over the indexes introduced in this study allows us to discriminate effectively the subgraphs in which a new topic will shortly emerge from the ones of the control group. For example, Table 7 reports the pace of collaboration obtained for both debutant and non-debutant topics in 2004. If we consider a threshold of 0.41, our approach is able to select 8 out of 9 debutant topics, obtaining 89% precision and 100% recall. It should also be noted that since both the pace of collaboration and the density are time-dependent the threshold should also be set accordingly. Similarly, Table 8 shows precision and recall obtained by using a threshold over the collaboration pace in the years 2001, 2004 and 2006. In future work we plan to adopt more sophisticated statistical methods for detecting these topic graphs.

Table 7. List of topics, both debutant and non-debutant with their pace of collaboration analysed in the 2004.

Testing topic	Pace of collaboration	Debutant/Control
linked data	0.538	**D**
bilinear pairing	0.499	**D**
wimax	0.488	**D**
separation logic	0.463	**D**
phishing	0.446	**D**
micro grid	0.433	**D**
privacy preservation	0.426	**D**
vehicular ad hoc networks	0.416	**D**
mobile computing	0.409	C
electromagnetic dispersion	0.401	C
online learning	0.357	C
wavelet analysis	0.326	C
program interpreters	0.325	C
zigbee	0.313	**D**
natural sciences computing	0.308	C
knowledge discovery	0.300	C
fuzzy neural networks	0.298	C
three term control systems	0.250	C

Table 8. Precision and Recall when choosing particular thresholds for distinguish the classes of topics

Year	2001	2004	2006
Threshold	0.35	0.41	0.23
Precision	8/9	8/9	11/14
Recall	8/8	8/8	11/11

While these results are satisfactory, our analysis presents some limitations that we shall address in future work. In particular, we identified the relevant subgraph during the selection phase by simply selecting the *n* most co-concurrent topics of the topic under analysis. This solution allows us to compare graphs of the same dimension but presents two issues. In the first instance, it assumes all topics will derive from the same number of research areas, which is an obvious simplification. Indeed, emerging topics may have different natures, based on their origin, development patterns through time, interactions of pioneer researchers, and so on. Therefore, each of them will actually be linked to a different number of established research areas. A manual analysis on the data suggests that using a constant number of co-occurring topics is one of the reasons why the overall pace of collaboration and growth index associated to the emergent topics are not much higher than the ones of the control group. When selecting too many co-occurring topics, we may include some less significant research areas or some research area that started to collaborate with the topic only after its emergence. Conversely, when selecting too few topics, the resulting graph may exclude some important ones.

A second limitation is that the selection phase performed in our study could not be directly reused in a system to automatically detect embryonic topics, since it requires knowledge of the set of topics with which the embryonic topic will co-occur in the future. However, this could be fixed by developing techniques to select promising subgraphs according to their collaboration pace and density. Indeed, we are currently developing an approach to do so that first generates a topic graph in which the links are weighted according to the collaboration pace and then exploits community detection techniques for selecting candidate sub-graphs to further analyse the dynamics discussed in this paper. This solution should be able to detect at a very early stage that 'something' new is emerging in a certain area of the topic graph, even if it may not be able to accurately define the topic itself. It would thus allow relevant stakeholders to react very quickly to novelties in the research landscape.

The findings of this study are also relevant to a number of research communities. Firstly, they appear to support our hypothesis about the existence of an embryonic phase in the lifecycle of research topics. Moreover, they bring new empirical evidences to related theories in philosophy of science, such as (Herrera et al. (2010)), Kuhn (2012), Nowotny et al. (2013), and Sun et al. (2013). Finally, they highlight that new topics actually tend to be born in an environment in which previously less interconnected research areas start cross-fertilising and generating original ideas. This suggests that interdisciplinarity is one of the most significant forces that push research forward, allowing to integrate a diversity of expertise and perspectives to come up with new solutions and new visions. The results of our analysis may thus support relevant research policies.

CONCLUSIONS

In this paper, we hypothesised the existence of an embryonic stage for research topics, in which they are not yet been labelled or associated with a considerable number of publications, and suggest that it is possible to detect topics at this stage by analysing the dynamics between already existent topics. To confirm this hypothesis, we performed an experiment on 75 debutant topics in Computer Science, which led to the extraction and analysis of a topic network including about 2000 topics, from a sample of 3 million papers in the 2000-2010 interval. The results confirm that the creation of novel topic is anticipated by a significant ($p < 0.0001$) raise in the pace of collaboration and density of the portion of network in which they will appear. These findings provide evidence regarding the existence of an embryonic phase, potentially allowing for a very early detection of research topics, bring new empirical evidence to related theories in philosophy of science and suggest that an interdisciplinary environment provides a fertile ground for the creation of novel topics.

We now plan to exploit the dynamics discovered in this study to create a fully automatic approach for detecting embryonic topics. We also intend to study and integrate a number of additional dynamics involving other research entities, such as authors and venues. The aim is to produce a robust approach that relies on multiple dynamics correlated with the emergence of new topics such that it could be used by researchers and companies alike for gaining a better understanding of where research is heading.

REFERENCES

Becher T, and Trowler P. 2001. *Academic tribes and territories: Intellectual enquiry and the culture of disciplines*: McGraw-Hill Education (UK).

Berners-Lee T, Hendler J, and Lassila O. 2001. The semantic web. *Scientific american* 284:28-37.

Blei D, and Lafferty J. 2006. Correlated topic models. *Advances in neural information processing systems* 18:147.

Blei DM, Ng AY, and Jordan MI. 2003. Latent dirichlet allocation. *J Mach Learn Res* 3:993-1022.

Bolelli L, Ertekin Ş, and Giles CL. 2009. Topic and trend detection in text collections using latent dirichlet allocation. *Advances in Information Retrieval*: Springer, 776-780.

Boyack KW, Klavans R, and Börner K. 2005. Mapping the backbone of science. *Scientometrics* 64:351-374.

Cano Basave A, Osborne F, and Salatino A. 2016. Ontology Forecasting in Scientific Literature: Semantic Concepts Prediction based on Innovation-Adoption Priors.

Cataldi M, Di Caro L, and Schifanella C. 2010. Emerging topic detection on twitter based on temporal and social terms evaluation. Proceedings of the Tenth International Workshop on Multimedia Data Mining: ACM. p 4.

Chang J, and Blei DM. 2010. Hierarchical relational models for document networks. *The Annals of Applied Statistics*:124-150.

Chavalarias D, and Cointet J-P. 2013. Phylomemetic patterns in science evolution—the rise and fall of scientific fields. *PloS one* 8:e54847.

Couvalis G. 1997. *The philosophy of science: science and objectivity*: Sage.

Davis JA, and Leinhardt S. 1967. The structure of positive interpersonal relations in small groups. *ERIC*.

Decker SL, Aleman-Meza B, Cameron D, and Arpinar IB. 2007. Detection of bursty and emerging trends towards identification of researchers at the early stage of trends. University of Georgia.

Duvvuru A, Kamarthi S, and Sultornsanee S. 2012. Undercovering research trends: Network analysis of keywords in scholarly articles. *Computer Science and Software Engineering (JCSSE), 2012 International Joint Conference on*:265-270.

Duvvuru A, Radhakrishnan S, More D, Kamarthi S, and Sultornsanee S. 2013. Analyzing Structural & Temporal Characteristics of Keyword System in Academic Research Articles. *Procedia Computer Science* 20:439-445.

Erten C, Harding PJ, Kobourov SG, Wampler K, and Yee G. 2004. Exploring the computing literature using temporal graph visualization. *Electronic Imaging 2004*:45-56.

Faust K. 2010. A puzzle concerning triads in social networks: Graph constraints and the triad census. *Social Networks* 32:221-233. http://dx.doi.org/10.1016/j.socnet.2010.03.004

Fusch PI, and Ness LR. 2015. Are we there yet? Data saturation in qualitative research. *The Qualitative Report* 20:1408.

Griffiths D, and Tenenbaum M. 2004. Hierarchical topic models and the nested Chinese restaurant process. *Advances in neural information processing systems* 16:17.

Gruhl D, Guha R, Liben-Nowell D, and Tomkins A. 2004. Information diffusion through blogspace. *Proceedings of the 13th international conference on World Wide Web*:491-501.

He Q, Chen B, Pei J, Qiu B, Mitra P, and Giles L. 2009. Detecting topic evolution in scientific literature: how can citations help? *Proceedings of the 18th ACM conference on Information and knowledge management*:957-966.

Herrera M, Roberts DC, and Gulbahce N. 2010. Mapping the evolution of scientific fields. *PloS one* 5:e10355.

Holland PW, and Leinhardt S. 1976. Local structure in social networks. *Sociological methodology* 7:1-45.

Jo Y, Lagoze C, and Giles CL. 2007. Detecting research topics via the correlation between graphs and texts. *Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining*:370-379.

Kamaliha E, Riahi F, Qazvinian V, and Adibi J. 2008. Characterizing Network Motifs to Identify Spam Comments. 2008 IEEE International Conference on Data Mining Workshops. p 919-928.

Kuhn TS. 2012. *The structure of scientific revolutions*: University of Chicago press.

Larsen PO, and Von Ins M. 2010. The rate of growth in scientific publication and the decline in coverage provided by Science Citation Index. *Scientometrics* 84:575-603.

Leydesdorff L. 2007. Betweenness centrality as an indicator of the interdisciplinarity of scientific journals. *Journal of the American Society for Information Science and Technology* 58:1303-1319.

Luce RD, and Perry AD. 1949. A method of matrix analysis of group structure. *Psychometrika* 14:95-116.

Lv PH, Wang G-F, Wan Y, Liu J, Liu Q, and Ma F-c. 2011. Bibliometric trend analysis on global graphene research. *Scientometrics* 88:399-419.

Mathioudakis M, and Koudas N. 2010. Twittermonitor: trend detection over the twitter stream. *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*:1155-1158.

Morinaga S, and Yamanishi K. 2004. Tracking dynamics of topic trends using a finite mixture model. *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*:811-816.

Newman ME. 2001. The structure of scientific collaboration networks. *Proceedings of the National Academy of Sciences* 98:404-409.

Nowotny H, Scott PB, and Gibbons MT. 2013. *Re-thinking science: Knowledge and the public in an age of uncertainty*: John Wiley & Sons.

O'Callaghan D, Harrigan M, Carthy J, and Cunningham P. 2012. Identifying discriminating network motifs in YouTube spam. *arXiv preprint arXiv:12025216*.

Oka M, Abe H, and Kato K. 2006. Extracting topics from weblogs through frequency segments. Proceedings of WWW 2006 Annual Workshop on the Weblogging Ecosystem: Aggregation, Analysis, and Dynamics.

Osborne F, and Motta E. 2012. Mining semantic relations between research areas. *The Semantic Web–ISWC 2012*: Springer, 410-426.

Osborne F, and Motta E. 2015. Klink-2: integrating multiple web sources to generate semantic topic networks. *The Semantic Web–ISWC 2015*: Springer, 408-424.

Osborne F, Motta E, and Mulholland P. 2013. Exploring scholarly data with rexplore. *The Semantic Web–ISWC 2013*: Springer, 460-477.

Osborne F, Scavo G, and Motta E. 2014. A hybrid semantic approach to building dynamic maps of research communities. *Knowledge Engineering and Knowledge Management*: Springer, 356-372.

Pham MC, Klamma R, and Jarke M. 2011. Development of computer science disciplines: a social network analysis approach. *Social Network Analysis and Mining* 1:321-340.

Pržulj N. 2007. Biological network comparison using graphlet degree distribution. *Bioinformatics* 23:e177-e183.

Rosen-Zvi M, Griffiths T, Steyvers M, and Smyth P. 2004. The author-topic model for authors and documents. *Proceedings of the 20th conference on Uncertainty in artificial intelligence*:487-494.

Salatino A. 2015. Early Detection and Forecasting of Research Trends. *ISWC-DC 2015 The ISWC 2015 Doctoral Consortium*:49.

Salatino AA, and Motta E. 2016. Detection of Embryonic Research Topics by Analysing Semantic Topic Networks. *2016 Workshop on Semantics, Analytics, Visualisation: Enhancing Scholarly Data (SAVE-SD 2016)*.

Sun X, Ding K, and Lin Y. 2016. Mapping the evolution of scientific fields based on cross-field authors. *Journal of Informetrics* 10:750-761.

Sun X, Kaur J, Milojević S, Flammini A, and Menczer F. 2013. Social Dynamics of Science. *Scientific Reports* 3:1069. 10.1038/srep01069

Tseng Y-H, Lin Y-I, Lee Y-Y, Hung W-C, and Lee C-H. 2009. A comparison of methods for detecting hot topics. *Scientometrics* 81:73-90.

Ugander J, Backstrom L, and Kleinberg J. 2013. Subgraph frequencies: Mapping the empirical and extremal geography of large graph collections. Proceedings of the 22nd international conference on World Wide Web: International World Wide Web Conferences Steering Committee. p 1307-1318.

Wu Y, Venkatramanan S, and Chiu DM. 2016. Research collaboration and topic trends in Computer Science based on top active authors. *PeerJ Computer Science* 2:e41.