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Evaluating technological emergence using text analytics

two case technologies and three approaches

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Abstract Scientometric methods have long been used to identify technological trajectories, but we have seldom seen reproducible methods that allow for the identification of technological emergence in a set of documents. This study evaluates the use of three different reproducible approaches for identifying the emergence of a technological novelties in scientific publications. The selected approaches are term count technique, the Emergence Score (EScore) and Latent Dirichlet Allocation (LDA) We found that the methods can uncover the emergence of technology from different vantage points. Term count based method identifies detailed emergent pattern. EScore is a complex bibliometric indicator that provides a holistic view of emergence by considering several parameters, namely the term frequency, size, and origin of the research community. LDA traces the emergence at the thematic level and provides insights on the linkages between emerging research topics. The results suggest that term counting produces results practical for operational purposes, while LDA creates insight at a strategic level.

Keywords Technological Emergence · Topic modeling · Emergence score (EScore)

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1 Introduction

Technological emergence refers to the manifestation of a drastic change to the socio-technological status quo. There has been a long-standing fascination with the process of technological emergence. In 1902, [1] already argued that approaching the implications of new technologies in a systematic manner would enable a better society. Later, Schumpeter explained the phenomenon by defining "creative destruction, which is a cyclical process of new innovations that will be displaced by next generation of improved services or products. Recent literature has highlighted the importance of emerging technologies (ETs) through their characteristics. Various authors have argued that ETs offer a wide range of benefits to the economic sectors [2], create new or transform existing industries [3], have high disruptive potential [4], or can exert economic influence in the future [5].

Regardless of the recent efforts to define ETs, analyzing technological emergence can be seen as a pool of methodological approaches rather than a rigorous theory and set of reproducible methods [6]. Theoretically, the discussion on technological emergence is linked to the literature on technological change, for example, the evolutionary theory of technological change (ETTC) or technological innovation systems. ETTC offers a biological evolution analogy to understand the emergence and development of complex technological systems, and other schools of thought apply different lines of reasoning. Focusing on the methodological elements, multiple methods have been used to model the path of technological development. Probably the most well known is the "workhorse" of technological forecasting—trend extrapolation [7].

Although we can easily understand how the selection process explains the survival of the fittest, it cannot explain the arrival of the fittest. Arrival, or emergence, as we would rather call it, is a term used to define "the arising of novel and coherent structures, patterns, and properties during the process of self-organization in complex systems [8]. Working toward a robust operationalization of emergence, we look toward a proxy that would explain the arrival of the fittest. Therefore, we are relatively locked-in with the ex-post evaluation of emergence, but we want to be able to identify emergence as quickly as possible.

In the literature [6], it has been argued that emergence has five distinct characteristics, as follows: ostensivity, global presence, coherence, dynamism, and novelty. These elements of ET require us to identify examples (ostensivity), the large-scale adoption (globality and coherence), newness, and growth of an ET using a proxy measure. Large national and governmental programs, such as the European PromTech project[9] or Foresight and Understanding from Scientific Exposition (FUSE) research program, which was been initiated by the US Intelligence Advanced Research Projects Activity (IARPA) in 2011 and targets mining big data related to science and technology [6], have attempted to do just that. However, robust methodological approaches are seldom shown and tested in this arena.

Several approaches have, however, been proposed in literature. An emerging cluster model focused on near immediate identification or predictive analysis of emerging clusters based on patent citation data [10, ?]. This approach is with limitations due to the different approaches to patent citations in different regions [11], which limit the methods applicability. Text mining has been seen as a particularly "effective means" [12] for detecting novelty. A particular advantage is the reliance on the text of the author, which can be taken to include the voice of person carrying out the novelty creation. As seen in Gerken et al. [13] recent literature in novelty detection has focused on textual data, but limited to a significant extent to keywords or the Subject Action Object (SAO) structures.

This study adds to the existing literature on technological emergence by testing three different approaches to identify elements of emergence in a technology. Adopting the framework by Suominen [14], this study elaborates on how emergence can be measured by simple count-based measures, when additional information is integrated into the simple counts and when a machine learning algorithm is used. This approach enables evaluating at which level of analytical complexity emergence can be detected. Using well-documented case studies on two technologies, light-emitting diodes (LEDs) and Flash memory, the results highlight how different approaches toward analyzing emergence can yield different outcomes. The objective is not to rank methods based on their superiority among the selected methods, but rather to show how these three approaches to measure ETs could differentially inform science policy, R&D management, and competitive technical intelligence.

The results suggest that methods should be selected based on their intended use, and that even relatively simple approaches can yield practical results. Calculating TF-IDF weighted term delta values by year resulted in highly detailed emergent pattern identification. The emergence score (EScore) builds on the expectation of coherence and stability in picking up novelty, creating needed stability in the measures. Finally, Latent Dirichlet Allocation (LDA) creates a baseline for strategic visual mapping that allows changes in the R&D landscape to be tracked, but has difficulty highlighting rapid small shifts.

2 Background

2.1 Operationalizing technological emergence

There is a strong body of literature that considers how we can measure technological progress. Such research has developed from the work of [15] in 1969 to the published book in 2011 by [16] on managing and forecasting technologies. To track and forecast technological change a number of methods and data sources have been used [17]. Methods have considered technological options [18, 19], technological systems [20], and most notably, the S-shaped growth curve [21]. However, in this body of literature, the specific issue of emergence and how it can be operationalized has received relatively little attention[1].

Scholars have focused on emergence as a construct, as in [8, 22], and as a case study operationalization, as in [23, 24]. The managerial utility of emergence comes from a better understanding of the radical and disruptive shifts occurring in industry and society as a whole (for a discussion on radical innovation and emergence, refer to [25]). The textbook approach to analyzing emergence has been using one variable, such as publication count, and extrapolating it to the future [7, 16]; although more complex multi-variable and machine learning–based approaches have been proposed, such as in [26]. Developing practical emergence detection methods is very much a work in progress. This prompts us to look at the elements of emergence to better understand how it can be operationalized.

As mentioned above, emergence is seen through five characteristics, namely ostensivity, global presence, coherence, dynamism, and novelty. It is a measuring problem, as we have uncertainties about what we are measuring. ETs are a complex whole bound in both time and place (for a discussion, refer to [27]); thus, we must rely on the emergent revealing itself. This behavior, referred to as ostensivity, is one of the key aspects of emergence. Ostensivity is based on the emergent being both novel and resulting from a dynamic process in a complex system. Even if we were able to identify parts of the whole and model parts of the system, it is ultimately the whole that creates the emergent. Templeton and Fleischmann [28] operationalized the ostensive properties of an ET via a map of science and technology.

The characteristics of an ET also require that there is a global presence, although this notion has been critiqued [23]. A global presence does not mean that a technology should be adopted equally everywhere, which may even be impossible [27]. Rather, this characteristic expects an emergent to be known broadly, rather than just within a micro-level social structure. This point should hold even if the ET's applicability is only in niches. The expectation of macro-level knowledge of an emergent also links to the expectation of coherence. That is to say, post-emergence, the emergent science or technology should be somewhat stable and reflect a shared view on how people understand it. The five characteristics described above lay the foundation for a framework for analyzing technological emergence.

2.2 Text Mining and Technological Emergence

Text analytics based methods have opened up new opportunities in the process of detecting ETs. Text mining refers to the process of extracting the knowledge or nontrivial patterns from text documents [29] and converting high-dimensional text to representable units with fewer dimensions, while keeping

[1] This was the subject of discussion during the 2017 PICMET conference that hosted a track and round table on technological emergence

the important information. The concept of "tech-mining" [16] has been defined as "the application of text mining tools to science and technology information, informed by understanding of technological innovation processes. The core functionality of a text-mining system lies in the identification of concept occurrence patterns across a document collection [30]. In practice, text mining utilizes term count or algorithmic approaches to identify distributions, frequent sets, and various associations of concepts at an inter-document level, thereby illustrating the structure and relationships of concepts as reflected in the corpus [30]. The major challenge in text mining arises from the high dimensionality associated with natural language, where each word from the text is considered a variable representing one dimension. To model technological emergence, a text mining process is required to reduce the dimensionality of the data to proxy measures that can highlight the characteristics of an ET.

The most elementary approach of using text mining to track technological emergence is the identification of novel terms that become prevalent as time goes on[**?**]. This type of elementary approach focuses simply on the emergence of novel concepts. The assumption is that these terms can be used as proxies that are able to describe the emergent aspects within a technological field. More complex approaches to understand technological emergence either add additional data or use more advanced methods to analyze the count of terms in a given set of documents. For instance, text-based similarity measures combined with citation information used to identify the degree of knowledge flow between documents [31]. Patent text analysis using patent co-classification was used to expose the uncertainty of ETs in the field of cellulosic bioethanol [32]. Methodological complexity has been added by, for example using "k nearest neighbor" to conduct technology opportunity analysis using patent text [33]. Text summarization and angle similarity measures have been applied to map patents and technological pathways [34,35]. Latent semantic indexing (LSI) was used to grasp the patent and paper concept similarity, which may provide insights on the detection of technological opportunities.[36]

As computational capabilities have increased more complex analysis processes that depart from simple term count based measures have become widely used. The most common approach might be LSI [37]. This is based on singular value decomposition (SVD), and it represents an extension of vector space model (VSM). Another classical approach is PCA [38]. However, these methods suffer from excessive information loss while pruning the data dimensions; moreover, they cannot account for the correlated words in the corpus's given lexicon. In other words, the methods are less accurate because they cannot address polysemy (words with multiple meanings) and synonymy (multiple words with similar meaning).

The focus of more recent dimensionality-reduction algorithms has shifted from traditional models to probabilistic methods. Probabilistic LSI (PLSI), a method proposed by [39], was a significant step forward in text analytics. It provides a probabilistic structure at the word level as an alternative to LSI. Its modeling draws each word of a document from a mixture model specified via a multidimensional random variable. The mixture model represents the topics. Therefore, each word originates from a single topic, and different words of one document can be drawn from various topics. However, PLSI lacks a probabilistic model at the document level. Documents in PLSI are represented as a list of numbers, with no generative probabilistic model for these numbers. This causes problems like over-fitting, as the number of parameters will grow linearly with the corpus size. Another problem is PLSI's inability to model documents outside the training set.

The LDA method, proposed by [40], can overcome the limitations of PLSI, providing a probabilistic model for document- and word-level analysis. LDA is a generative probabilistic model that draws latent topics from discrete data, like textual data. LDA relates documents, which are represented as random mixtures of latent topics, to each topic, and the topics are based on distribution of the words. The LDA probabilistic model and its extensions have been applied by several scholars to address the scientometric research questions. In [41], the authors have extended LDA by adding author information to create author-topic model. The primary benefit of the model is predicting the future research theme of specific scientists. [42] showed that the topic modeling outperforms the co-citation approach in producing distinctive maps of author-research relatedness. The classification of large text corpora is another stream of Scientometric research that has been applied via LDA for mapping scientific publications [43,44], topic based classification of patents [45,46], and clustering biomedical publications [47].

This paper examines to what extent emergent pattern are visible through the use of term proxies derived from scientific literature. The analysis looks at both ostensivity, the appearance of an emergent, and growth of any emergent pattern and how these are visible with different methods. This study analyses, as a baseline, an elementary term count based approach, a more complex approach incorporating control parameters for term emergence and finally a probabilistic based method. The capabilities of the methods are evaluated against two well–documented case studies, looking to qualitatively identify expected patterns of emergence.

2.3 Case Technologies

2.3.1 Light-emitting Diodes

Light-emitting diodes (LEDs) represent an application of semiconductor technology that emits light when activated. The technology has had several advantageous applications over several decades. As a component, LEDs have been available since the 1960s, but due to the limitation of the technology, LED applications have been restricted to small indicator lights. The first LED, presented in 1962 by [48], had a luminous efficiency of 0.1 lm/W. More recent developments have led to white LEDs, which have a greater luminous efficiency, enabling LEDs to be used for lighting.

The technological pathway of LED technology was founded on advancements in semiconductor technology. While the capacity to emit visible light was well known, the ability to create LEDs that could be utilized in practical applications required stable processes for manufacturing semiconductors. Although LEDs were used as indicators during the late 60s, it was the rapid development in semiconductor technology that resulted in a near order of magnitude development in the lm/W efficiency of LEDs [49].

Even the order of magnitude development was not enough to create the white light that could serve as a replacement for the dominant lighting technologies. White light was produced by either combining red, green, and blue LEDs or using phosphorous material to convert a blue or ultraviolet (UV) LED to a white lightemitting one [50]. The required technological breakthrough came with the work of [51, 52]; this advancement enabled a gallium nitride-based blue and green LED. This invention enabled the development of white LEDs with the technological capability of replacing existing the dominant technology. Haitz's law was used to model the exponential rate of lumen/watt efficiency development of LEDs; this law expects the efficiency of LEDs to double every 36 months, but through 2020, the development of LEDs is expected to reach a phase where they "approach the end of the efficacy ladder and meet or exceed the market's needs with respect to cost and quality" [53].

LEDs offer an interesting Scientometric case technology, as we can easily identify interesting points in the technological trajectory. We can pinpoint the beginning of the technology to Russia in 1927 [54], a major inflection point that started with the invention of [51] and near-exponential trajectory of technological advancement that is now nearing its end [53].

At the current status of the LED, or solid state lighting (SSL) technology, much seems to have been accomplished, but the literature still expects new patterns to emerge. [53] suggested a major current advancement in the domain relating to improving the lifetime of LEDs, for example, by reducing efficiency losses due to semiconductor heating. Another avenue of LED development consists of broad complementarities where LEDs are either applied or enable other technologies to evolve. These include a "distributed last-meter for sensors, actuators, communications, and intelligence for the Internet of Things," water-purification, fiber-optic communication, or power electronics [55].

2.3.2 Flash memory

Flash memory is one technology in the continuum of development among memory cell technologies. Semiconductor memory cells can be divided into two main categories, namely volatile and nonvolatile memory. Volatile memory, including SRAM and DRAM, enables fast reading and writing, but it loses its data when the power supply is turned off. Nonvolatile memory (NVM), such as Flash memory, can sustain data even without a power supply. Mainly due to this characteristic, NVM has several applications. Flash memory has enabled the growth of portable electronic adoption, as it offers a practical compromise between size and flexibility. Flash memory is used for two major applications, namely code storage and data storage. As the need for these applications increases, the demand for Flash memory also increases [56].

Its origin can be tracked to a patent by [57]. The technology was seen to overcome significant challenges of EPROM, the dominant technology at the time, as it is much more reliable. Soon after its invention, several publications expressed the expectation that Flash memories would be rapidly adopted [58, 59]. The technology faced reliability issues that kept market penetration relatively low [60]. Early market predictions were modest, keeping expectations regarding Flash memory relatively limited. In the mid-1990s, Flash memory was expected to occupy a market share of 6% by 2000. Since then, two dominant Flash architectures have emerged, as follows: NOR Flash, designed for code and data storage, and NAND Flash for data storage [56]. These developments changed the the game for Flash memory.

The abilities of NOR and NAND Flash memory increased the market size of the technology. Flash memory is currently used, for example, in solid-state disks, which take advantage of its small dimensions, low power consumption, and lack of mobile parts. With an increase in the number of applications exploiting the benefits of the technology, Flash memorys market share has increased. Since 2000, Flash memory technology has been seen as a mature technology, which has increased rapidly in market size [56].

Whereas SSL technology seems to be the end of the line for lighting technology [53], this is not the case for flash memory. With the ever-increasing demand for data storage, the sizes of Flash memories have increased. Unfortunately, the size of a Flash memory has been seen to correlate with an increase in latencies and data errors, creating a nearly unbreakable roadblock for the technology. Some suggest that the technology will be unable keep up with users' needs by 2024.

Several options have arisen to take the place of Flash memory, within the family of Non-volatile memories. Among these are magnetoresistive random-access memory (MRAM), phase-change random-access memory (PRAM), siliconoxidenitrideoxidesilicon (SONOS) and resistive random-access memory (RRAM). Of these technologies, MRAMs represent a near-to-market technology that is being manufactured and applied in niche applications [61]. PRAMs are also near to market, but they are also undergoing heavy research [62], and they are expected to solve the key issues currently restricting Flash memory technology. Finally, RRAM is at the demonstration phase. Research suggests that it will have a simpler structure than MRAMs, while it will be faster than PRAMs and offer smaller latencies and lower power consumption compared with Flash memory [63, 64, 65].

3 Data collection and methodology

This study uses LED and Flash memory technologies as two case studies, and the aim is to examine the performance of three approaches for the detection of relevant topics or possible ETs. The scientific publication data related to LED and Flash memory were gathered via a Boolean search algorithm from the Web of Science (WOS) core collection database in December 2017. The search query for LED technology was formed on variations of LED [2], while that for flash memory[3] was based on keywords. The search queries were applied to titles, keywords, and abstracts of publications in the English language. The timespan of the search query was through 2016, without any restriction on the starting publication year. The searches returned 65,222 and 13,507 records related to LED and Flash technology, respectively. The retrieved data were imported into VantagePoint software to consolidate duplications and author name variations, as well as to prepare the data for running the e-score algorithm. After cleaning, especially in terms of eliminating non-Flash-related biomedical papers, the Flash dataset was reduced to 10,968 records.

Central to the evaluation of the selected methods is to understand the cases at hand. The previous sections gave a brief introduction to the technologies and the emergent factors expected to occur in the data. Evaluation of the different methods is done using a qualitative approach relying on a framework of expected emergent behavior in the data. Each method is evaluated separately and compared on the basis of theoretical and managerial implications.

The evaluation framework is based on Table 1. This table is used to identify, if an emergent topic is identified by the three utilized method or not. For both LED and Flash memory technologies the table gives an overall categories of concepts and probable terms associated with these technologies. These concepts have been created based on the authors careful reading of recent publications in the case study domains and knowledge of the technologies. The probable terms have not been used as an exhaustive list, but terms identified to be emergent by different methods were evaluated individually by relying on the data (articles abstracts) downloaded and online searches, if needed. For LDA this meant looking a high probability terms in topics as a whole. Overall, the term mentioned guide the evaluation process to look for particular emergent patterns in the case technologies within the last ten years.

3.1 Emergence Score Algorithm

Previous text mining–based indicators designed for tracing ETs were formulated using citations or textual parts of documents. Indeed, these methods may have overlooked the role of other bibliometric variables, such as authorship information. The emergence score (EScore) [66] traces ETs at a micro-level (technology level), incorporating authorship information and thresholds for time of publication. The EScore's functionality corresponds to the major attributes of ETs defined in the literature [67, 23, 3, 5].

[2] TS=((”light-emitting diode*” OR ”light emitting diode*”) OR (”diode*” AND ”LED*”))

[3] TS= (”flash memor*” or ”memory cell*”)

Table 1: LED and FLASH technology emergent categories and a non-exhaustive list of concepts.

Technology	Category	Concepts
LED	Efficiency	thermal, heat, management, dissipation, efficiency loss and different chemical compounds, spectrum
	Sensors and actuators	sensors, internet of things, actuators,
	Communication	optic, sensor, transimission, communication, transmission speed, transmission efficiency
	Purification	UV range leds, water
FLASH	MRAM	magnetic, ferromagnetic, magnetoresistive effect, spin-transfer torque (STT), thermal assisted switching
	PRAM	PCM, PCME, PRAM, PCRAM, OUM, C-RAM, CRAM, chalcogenide, phase-change, memristor
	RRAM	ReRAM, memristor, dielectric
	SONOS	silicon nitride, SONOS, MONOS, charge trap flash

The EScore is a built-in module in the VantagePoint software program `www.theVantagePoint.com` [68]. The EScore algorithm is developed based on four major attributes of an ET, as follows: novelty, persistence, and change rates. The notion of novelty is related to discontinuous innovations [3] or putting an existing technology to a new use [69]. To operationalize the persistency attribute, the EScore algorithm considers terms that occur in a minimum of seven records published over at least 3 years; thus, the persistency measure ensures that the term is not a one time hit. To assure the novelty and growth characteristics, the ratio of records containing the term in the active period to those in the base period must be at least 2:1. Finally, the measure focuses on the change rates of terminology with the mentioned controls.

The last defining attribute of emergence is community, explained as coherence by Rotolo and colleagues [67]. The concept of community suggests that a number of professional researchers engaged in the topic and connections among them are necessary while an emerging technology is evolving. The EScore algorithm selects those terms associated with more than one author who does not share the same record set. In this study, the EScore serves as a metadata base emergence indicator.

3.2 Text preprocessing for count based analysis and LDA

The preprocessing for the LDA and term count based analysis was implemented in the Python programming language using existing software packages to clean the textual data. First, the datasets were processed using the Part-of-Speech tagging implemented in the NLTK package. The abstracts of the documents were analyzed and only the tags NN (noun, common, singular or mass), NNP (noun, proper, singular), and JJ (adjective or numeral, ordinal) were kept in the analysis. Thereafter, the abstracts were analyzed to remove terms containing numbers, stopwords, and punctuation. The size of the token bag for LED is 94 885 unique tokens and for Flash 21 320 unique tokens.

3.2.1 Count and TF-IDF weight based analysis

Term count based analysis is used as the most elementary approach to analyzing emergence using terms as the unit of analysis. The analysis was implemented using the pre-processed abstract and calculating Δ for all word tokens w appearing in year t and $t-1$. For each w Δ is word frequency $f_t - f_{t-1}$. Words that do not appear at two consecutive years are excluded.

Similar calculation is done using term frequency and inverse document frequency (TF-IDF) weighting scheme. Prior to calculating Δ for each w the frequency calculation were transformed to TF-IDF score weights using the Gensim package [70] in Python. After calculating the Δ values for LED and Flash token bags yearly, the tokens were sorted by to highlight the highest Δ values.

3.2.2 LDA procedure

The LDA algorithm was implemented in Python using an online variational Bayes algorithm [70]. The algorithm goes through the input tokenized data in chunks, updating the model as new data are analyzed, allowing for a relatively large corpus being run with a relatively small computation effort. LDA relies on its formal framework to model the input data, but it requires the user to set the number of topics produced as an output. Selecting a practical number of topics has been discussed in the literature. [71] looked for a trial-and-error method, testing different numbers of topics with given input data to produce the results that would be most convenient for human interpretation. Furthermore, research has shown a number of other mathematical approaches, such as using Kullback–Leibler (KL) divergence [72] to estimate the input. In this study, we implemented KL divergence to estimate the number of topics in the corpus.

For the datasets, the KL divergence was calculated for topic values ranging from 1 to 100. The upper bound was set somewhat arbitrarily based on the experience of running an analysis with different corpus sizes. Figures1 and 2 show the plot of values returned by the KL divergence function . Estimating the number of topics requires human intervention, as simply taking the smallest value of the series is not sufficient. Even if the researcher has a relatively narrow window of expected topics, automating the evaluation of a KL divergence plot can be challenging. In the case at hand, the number of topics selected for the analysis was 15 topics for Flash memory and 8 topics for LEDs. This selection

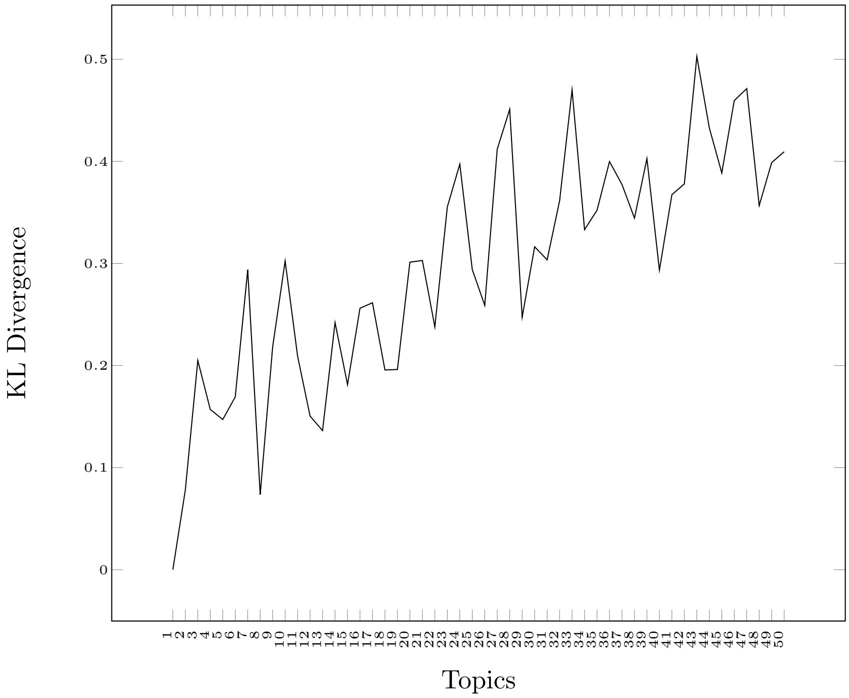

Fig. 1: KL Divergence for LED dataset

was based on the sharp value decrease of the KL divergence and subsequent testing of different topic parameters.

LDA creates two matrices, one for document probabilities and one for word probabilities. The former matrix contains the probability distribution of each record that belongs to one of the topics, while the latter contains the probability distribution of words in the corpus and their association with each topic. The topic probability distribution of each document, omitting small probabilities, was used to create a directed network. In the network, nodes are latent topics created by the algorithm and individual documents in the dataset. The edges between the nodes are directed from document to topic and the weight of an edge is defined by the probability of the document belonging to a certain topic. The word probability distributions were used to create word clouds to evaluate the content of the generated topics. The top 50 words were used to create the word cloud. In the word cloud visualization, the size of the words is based on their probability in a topic. The content and coherence of the topics are also evaluated using the word cloud plots. The assessment of the topical coherence is done by, first evaluating how concentrated the topics are to have high probability in only one or a few words.Second the topics are screened against expert human judgment to evaluate how semantically cohesive the topics are[71].

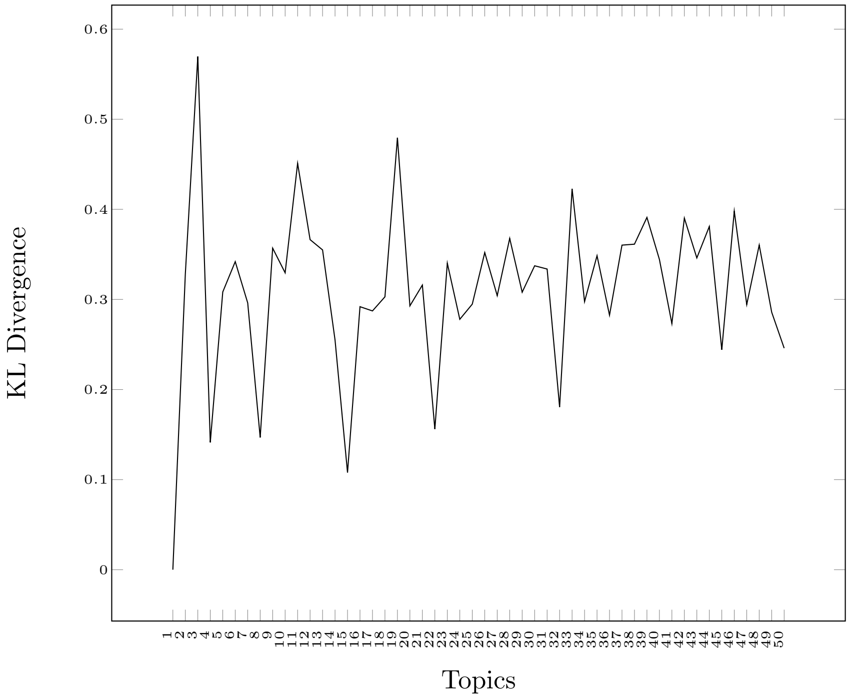

Fig. 2: KL Divergence for Flash memory dataset

The LDA framework does not include a temporal constraint. The algorithm is unaware if the documents in the corpus are spaced differently in time. Thus, information on each document's year of publication is included in the results ex post. Using the publication year of each record and the document topic probability matrix, the results are aggregated to a year to topic matrix, A, where Aij is the sum of probabilities of year i records over latent topic j. Finally, the year to topic matrix is aggregated using the soft clustering of topics, creating a year to cluster matrix. The year to topic and year to cluster matrices are used to uncover topics that grow over time to find potentially emerging topics.

The LDA soft classification is used to create a network representation. The result can be defined as an undirected bipartite graph. In a bipartite graph, nodes can be divided into two disjoint sets, U and V. Within the disjoint sets, each edge connects a node in U to one or more nodes in V. By definition, a bipartite graph is a graph that does not contain odd-length cycles. Focusing on the documents to topic probabilities produced by LDA, we can define $G = (U, V, E)$, where U represents documents, V topics, and E document topic probabilities. Focusing specifically on communities and the interaction between either set, we can use existing network analysis methods to transform the network to monopartite (one-mode) projection and find communities in either the bi- or monopartite graph.

4 Results

4.1 Emergence Score Results

The results of the EScore algorithm for Flash memory data are presented in Table 2. The top 10 emerging terms are illustrated in the first column. The keyword solid state drive (SSD) is at the top of the list. SSD in an application of the Flash memory cell, and it is currently fully commercial. Arguably, the term appears here due to the overall increase and terminological cohesion in memory technologies. More interesting are the new technologies, such as the PRAM and RRAM, that are also highlighted in the results. This suggests that EScores can pinpoint emergent patterns. However, as relatively well known and common terms also appear, the analyst is required to handpick novel terms. The top organizations active in the mentioned emerging fields, for instance, are Chuo University, Bne Gurion University, Caltech, and the University of Tokyo. The top countries in order of EScores are China, the United States, Israel, and South Korea. The top three researchers are Ken Takeuchi, Moshe Schwartz, and Shubei Tanakamaru.

The implementation of the EScore algorithm for the LED dataset provided the results shown in Table 3. Several word combinations appears at the top of the list; for instance ”visible light communication” (VLC) is a data transmission system that uses LED for communication rather than illumination. The idea behind building VLC systems using LEDs is to transmit data as fast as the speed of the light. The second emerging term is ”organometal halide perovskite,” which was used for the fabrication of bright LEDs in a 2014 report in *Nature* [73]. Here, organometal halide perovskite was used instead of the old direct-bandgap semiconductors, which are not economical for use in large-area displays. “Graphene,” the sixth emerging term, allows for tuning the color of LED light [74]. The next emerging term is “phosphorescent organic LED,” which is still a technology under research and development. The top three active participants in ETs in the LED domain are the Chinese Academy of Science, Pukyong National University, and the University of the Chinese Academy of Science. The top countries are China, South Korea, India and the United States. According to the EScores, the top authors are Remping Cao, Jung Hyun Jeong, and Sujan Rajbhandari.

4.2 Term count based results

The analysis of LED and Flash memory data produced two tables for both technologies (See A), one with simple term count values and one with values based on TF-IDF weighting. For Flash memory, the results for TF-IDF (Table 5) weighted and count based are very different. For TF-IDF results, the table highlights several technical aspects of Flash technology that could be regarded as emerging at their time. For example between 2006–2007 “tcnq”, used as silver–tetracyanoquinodimethane, has been noted in the development of novel memory types [75]. Similar examples can be highlighted for several years such as “nanocrystal based” [76], “SiNx”, “Fullerene” [77] among other detailed material options that have been reported to change Flash memory technology. The TF-IDF weighted results also have a number of references to new technologies, such as STT RAM or Spintronics referring to spin-transfer-torque memories [78] and siliconoxidenitrideoxidesilicon (SONOS) memory cell [65], error correction issues such as “RTN” (Random Telegraph Noise) [79] or “SEUs” (Single-Event Upset) [80]. The results for the TF-IDF weighted Δ values show clear emergent terms with significant detail.

This is not the case for the count based values. Seen in Table 6, the count based values only produce general terms like “memory”, “flash” or “voltage”. In addition to the general terms, the count based values yield some terms that could be regarded as stop-words. A notable exception to the general terms are SEUs, also seen in th TF-IDF weighted result.

For LEDs the case is similar to the result of flash memory analysis. Using TF-IDF weighting the results show the individual materials used for enhancing of LEDs performance. Examples in the Table 7 are ZnTe [81], quinacridone [82], or Organoboron [83]. In addition to materials that would yield better efficiency the table contains multiple LED components enabling better performance, such misorientation in LED manufacturing [84] or microball lenses [85]. The table also highlights application areas of LEDs, such as LEDs in microscopy [86] and communication [87].

Similar behavior as with the Flash memory dataset (see Table 8), the count based analysis of the LED data remains at an high abstraction level . Although issues highlighted in the background as being emergent, such as “temperature” is in the table, the table yields little value in identifying detailed emergent issues. It seems that a relatively simple rate of change based analysis yields relatively detailed results when using TF-IDF weighting. Obvious from the table is that the count based and TF-IDF tables for either of the technologies shared little terminology. Also, with TF-IDF terms change significantly between the evaluated time slices. This raises some questions of the stability of the approach.

4.3 LDA results

The analysis of the LED dataset produced eight topics and a bipartite graph linking the documents to topics. Word clouds were used to describe the content of each node. The eight topics produced via LDA showed different thematic areas of research, described by the word clouds in Figure 3. Topic 1 is related to the light-emitting system, design, and different relevant modules. Topic 3 focuses on phosphor, which is a key material related to LED performance. Phosphor’s material, chemistry, and composition determines the efficiency, light quality, and stability of the LED light. Topic 4 focuses on the emission spectrum, that is, the spectrum of frequencies emitted by the LED. This is central to understanding of how an LED operates. Topic 5 focuses on the interplay current and efficiency of LEDs. When an LED's current increases, its efficiency drops; this is due to electron leakage, and it represents one of the major obstacles for creating long-lasting, and high–lumen output LEDs. The cause of this inefficiency was identified in the late 1990s and the solution was only discovered as early as the 2010s [88]. Topics 2 and 6 look at a particular stream of LED research that focuses on organic LEDs (OLEDs). These are LEDs in which an organic compound is the source of the emission. In OLEDs, there is a specific polymer-based solution. The term "polymer" can also be seen in Topic 6 (3f). Both Topics 7 and 8 focus especially on the LED substrate. In these topics, we can identify two central materials, zinc oxide (ZnO) and gallium nitride (GaN), which are the core of making better white LEDs. The substrate material used is an ongoing research topic in the LED industry, and the search for a dominant solution continues [4].

The soft classification of LDA was converted to a bipartite graph, embedding the metadata of publication year into each document node. This enabled visualization of an overlay of what has changed in the graph from overall to 2015 onward. The bipartite graph consists of 56,985 nodes and 455,816 edges connecting document nodes to topic nodes. The bipartite network was converted to the one mode, representing only linkages and sizes of topics. The one-mode transformation showed three central nodes, namely Topics 4, 6, and 8. These are large topics, but they are also heavily linked via shared probabilities among the documents. The network created is shown in Figure 4. The one-mode network illustrates the significant interest towards OLED technology (Topic 6), analyzing its capabilities (Topic 4), and material options related to the technology (Topic 8).

Focusing on emergence, for each topic, we calculated its relative growth in importance. Thus, the relative share of growth in the topic probability assignments per year is seen in Figure 5. Here, we identify the emergent pattern, as only two topics increase in relative importance, namely Topics 6 and 4. From these, the important topic is Topic 6, which focuses on OLED. This is to say, by using LDA, the emergent technological option highlighted is OLED technology.

For Flash memory, the KL divergence value suggested that 15 latent topics could be derived from the dataset. When modeled using LDA, we identified clear patterns, as shown in Figure 6. In the analysis, although concerted efforts were made to exclude medical research from the dataset, Topic 1 is an outlier relating mostly to medical technology. Topic 2 emphasizes the term "resistive, rram," which refers to the new generation of memory technology known as resistive random access memory (RRAM). RRAM is known as a breakthrough NVM technology and the most promising candidate for the next generation of

[4] https://www.ledinside.com/showreport/2015/4/manufacturers_divided_about_gan_led_chip_technology

memory [89]. RRAM has a very low operation voltage, while it performs faster than previous generations, with higher reliability [89]. It has significant potential for commercialization in the future [89]. Topic 15, with the top words of "change, resistance, phase," is related to Phase-change random access memory (PCRAM) technology, which may also have a promising future [90]. Topic 3 is related to the area of SSD configuration and power management. SSD is a storage device that includes an integrated circuit assembly that stores the data. The top words in Topics 4, 11, and 14 are "power, high, voltage, consumption, charge, device." These topics cover the research about the settings of voltage thresholds and power management, which play an important role in Flash performance [91]. In fact, the voltage threshold approach can influence the performance and reliability of Flash memory.

Topic 5 (see Figure 6), with top terms like "sensor, design, architecture, system," can be associated with the Flash memory storage system used in modern wireless sensor devices. Flash memory has become a prevalent storage medium for sensor devices because of its beneficial features, such as non-volatility, small size, light weight, fast access speed, shock resistance, high reliability, and low power consumption[92]. Topic 7 highlights terms like "process, zno, DRAM," which relate to a new generation of NVM known as zinc-oxide (ZnO) charge trapping memory cell Flash technology [93]. Topic 8 is about static random-access memory (SRAM), which is a type of a memory used in a computer's cache memory. Topic 9 corresponds to NAND Flash memory, while Topic 10 is about the garbage collection (GC) process in NAND Flash memory, which secures the free space prior to writing new data. Topic 12 demonstrates recent research on graphene. In terms of Flash memory, graphene possesses unique properties, such as a high density of states, high work function, and low dimensionality, which can enhance Flash memory performance [94].

Topic 13 (see Figure 7) is represented with top terms like "delta, magnetic, layer, memristor," representing a mixture of major components or operation processes in Flash memory (e.g., oxide layer) and memristors. The word memristor is often used as a synonym for resistive RAM (ReRAM or RRAM). Research [95] suggested that memristors are expected to replace the NAND Flash memory in future.

The Flash memory topic bipartite network was transformed into a one-mode network to illustrate the relationship between the topics. The network graphs in Figure 8 show one large node, Topic 3, with 14 more equally sized nodes. The strong topical linkage between Topics 3, 4, 11 and 13 is due to the similarity in their themes. The focuses of these topics are Flash memory components, modes of operation, power management, memory architecture, or data storage configuration.

Highlighting emergence in Figure 9, we see several rapidly changing topics. For Flash memory, the importance of specific topics has been more dynamic. Of particular interest is the period of 2006–2007, in which several topics increased significantly, while others decreased in importance. For example, during this period, Topic 3, the largest topic by size , increased in importance, with significant reductions in importance of new-generation technologies, such as RRAM (Topic 2) or novel sensor applications (Topic 5). Turning our focus to recent emergent applications, we highlight Topic 12, which shows consistent, increasing growth in the two latest time slices. Topic 12 highlights graphene research, and especially, the application of graphene to form graphene Flash memory. This new material option has shown great promise in increasing the performance of Flash memory (e.g., [96]).

4.4 Comparison of results from selected methods

Table 4 shows the novel concepts and emerging terms in Flash memory and LED technology detected by selected three methods (EScore, LDA, count based). For Flash memory, EScore and LDA identified emerging PCRAM and RRAM field of research. In addition, LDA was able to show three more active research area about application of Flash memory in wireless sensor devices, zinc oxide charge trapping memory cell and utilization of graphene for development of new Flash memories. The terms detected by TF-IDF method are at detailed layers related to technical terminologies of the fabrication materials for enhancing the Flash memory performance. For instance TCNQ, Nanocrystal based, SiNx and Fullerene. The occurrence of these terminologies is associated to a certain time period presented in Table 5. Moreover, spin transfer torque and SONOS memory cells were identified by TF-IDF as novel technological alternatives for Flash memory in their corresponding time. The concepts and keywords detected by term count method were rather generic and not useful.

In case of LED technology (see Table 4), the LDA method seems to cover more recent emerging fields comparing to EScore and TF-IDF. EScore and LDA methods detected research development in phosphorescent organic OLED, VLC as a new application area for LED and usage of graphene for light tuning purposes. Only LDA algorithm identified the ongoing field of research in ZnO and GaN. In addition, EScore results shows research interested in organometal halide perovstike, which is an element that can be used for fabrication of LED for large scale displays. TF-IDF method presented particular terms related to novel materials or components for manufacturing of LED such as; ZnTe, quanacridone, organobron and microball lens.

5 Discussion

The major objective of this paper was to demonstrate and compare different approaches in detecting ETs in a scientific publication dataset. We examined the EScore indicator, unsupervised machine learning algorithms known as LDA and term count based methods. The EScore can be considered a two-stage indicator that involves several parameters (country, author information, keyword or abstract, year). It scores terms on their degree of emergence. Then, secondary indicators are composed to reflect the extent to which countries, organizations, or authors are publishing most actively using the emergent terms in their abstract records. The EScore algorithm's functionality is based on the recent theoretical definition of ET and its related attributes[67]. The unsupervised machine learning method is a generative model, and it tends to uncover latent patterns in the textual data. Relying on the frequency of keywords occurring each years, the term count based methods aim to identify technological novelty and ostensivity. The interpretation of the captured pattern to be translated to an ET depends on expert validation.

In practice, it is difficult to argue the superiority of one of these methods over the others. We, however, argue that measuring superiority is not necessary. All utilized methods in this study facilitate the recognition of emergent patterns in text and the navigation through the complex datasets by reducing noise embedded to them. The results gathered from the analysis of two different technologies highlighted that all three methods (EScore, LDA, and term count) view emergence from different vantage points. Even though not looking towards similar overlap in clustering as in [97] Table 4 highlights the overlap of the methods. The EScore algorithm traces the emergence from a bibliometrics point of view. LDA produces meaningful, large-scale topical changes and highlights the thematic concepts of the dataset; it also shows the topical change at the document level, as well as topical linkage. The TF-IDF weighted count method was able to yield very precise and detailed emergent terms. These methods have very different utility. From a managerial perspective, LDA offers a strategic level view with broad conceptual changes in the technological landscape. The TF-IDF based method was able to identify small details, probably more useful for operational purposes. EScoring embedded in a propriety solution offers robust results with, but not at either extreme or the abstraction level.

Moreover, one of the prominent advantage of LDA compared to EScore or count based methods is its focus on the context rather than keyword counts. LDA results provided the central topics of research for LEDs and Flash memory technology. Each identified topic created is based on a distribution of keywords. The interpretation for the appearance of each term within the topic can be done based on its neighboring keywords. For instance, the "Graphene" research topic has been detected by both EScore and LDA within LED technology datase . Based on the EScore table it is difficult to understand how Graphene is related to LED research. The only way is to track down the set of associated articles include Graphene in their abstract from the dataset. LDA makes interpretation easier by providing the relevant context for "Graphene" in Topic 8. In fact, Topic 8 is presenting the novel materials and chemical compounds used for fabrication of LED such as ZnO, GaN and Graphene. The application of LDA as an unsupervised learner on an unlabeled dataset can detect the central research topics and in detail answer questions of what is the role of Graphene in LED research without extra input from the user. For this reason we see strategic level technology management applications of LDA.

We argue that the selection of a specific method hinges on the intended use of the results. In some cases, the user may be interested in detecting a niche and ongoing area of research that has not yet become dominant knowledge in the scientific community. The sensitivity of the machine learning algorithm can be adjusted, such that it could be able to detect any topical outburst with smaller frequencies. For instance, if the model keeps the keywords with minimum occurrences in the preprocessing phase, the final results will include rare concepts/terms. The flexibility of setting preprocessing rules can expand the spectrum of the results by showing both new high-frequency terms and new rare terms. However, our results suggest that the extremely simple count based calculation is already extremely sensitive in tracking changing terminology.

It is clear that authors are not always consistent in using similar terminologies or jargon to describe the same phenomena, such as the use of the term memristor. The development of a consensus on terminology can take time. While the EScore criteria are also flexible in terms of assigning the term frequency threshold, one of the main ideas behind its design is focusing on persistent concepts rather than a one-time outburst. LDA, on the other hand, creates topics that can embed a variety of terms used to describe a particular emergent behavior. According to Kuhn [98], in the development process of any new science, there is progress on the emergence of esoteric vocabulary and skills, and a refinement of concepts that increasingly lessens their resemblance to their usual common-sense prototypes. The methods shown here have very different capabilities in identifying novelties. A purely term count based evaluation seems to be sensitive to small shifts. However, stability of the results is poor as highest Δ terms seem to appear and disappear on a yearly basis. The control parameters offered by solutions such as EScore can allow for stability without limiting detection of novelties.

The topical clusters and terms generated by LDA are purely based on documents' language, and they are independent of article's author, country, and citation information. This independence has pros and cons. The advantage of being independent of the citation and connection information among authors is that the phenomena of emergence or niche research will not be limited to a certain circle of the scientific community. Drawing from Kuhn's work [98], scientific knowledge is represented by vocabularies; thus, tracing the change within the language used by authors may lead to detecting the shift in their ideas. LDA is a tool that considers the language that represents old or new ideas. At the same time, the machine learning method used in this study overlooked the role of the research community, which is defined as one of the major attributes of ET [67].

This study is not without limitations. First, we only examined three methods in two technology cases. Adding more methods and case studies will surely provide more insight. Possible methodological addition could include, for example, one-class SVM, which has been used widely for outlier detection in computer science. For the case approach, LED and Flash memory have the attributes of an interesting case study, manufacturing a controlled test dataset could serve a purpose. We think that a synthetic dataset could yield a more controlled sample where the future development is still unknown.

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6 Reference

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A Results of term count based methods

Table 2: Emergence score results for Flash memory

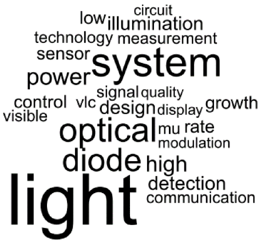
	Emerging technologies	**EScores**	**Top Organisations**	**Top Countries**	Top authors
1	Solid-state drive	6.043	Chuo Univ	China	Takeuchi, Ken
2	Rank modulation	5.651	Ben Gurion Univ Negev	USA	Schwartz, Moshe
3	Codes	5.01	CALTECH	Israel	Tanakamaru, Shuhei
4	Phase-change memory	5.004	Univ Tokyo	South Korea	Sun, Chao
5	RRAM	4.691	Technion Israel Inst Technol	Japan	Bruck, Jehoshua
6	Memristor	3.624	Chongqing Univ	Taiwan	Yamazaki, Senju
7	SRAM cell	3.467	Univ Sci & Technol China	India	Dolecek, Lara
8	Flash-Memory	3.466	Seoul Natl Univ	Singapore	Zuolo, Lorenzo
9	Error-correction	3.214	Texas A&M Univ	Canada	Matsui, Chihiro
10	Parity-check codes	2.96	Univ Calif Los Angeles	Iran	Tokutomi, Tsukasa

Table 3: Emergence score results for LED dataset

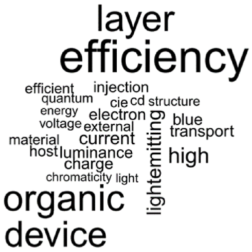
	Emerging technologies	**EScores**	**Top organisations**	**Top countries**	**Top authors**
1	Visible light communication	26.275	Chinese Acad Sci	China	Cao, Renping
2	Organometal halide perovskite	18.002	Pukyong Natl Univ	South Korea	Jeong, Jung Hyun
3	Sensitized solar-cell	17.884	Univ Chinese Acad Sci	India	Rajbhandari, Sujan
4	Delay fluorescence	17.881	Jinggangshan Univ	USA	Ghassemlooy, Zabib
5	Eu3+ ion	12.282	China Univ Geosci	Taiwan	Lin, Jun
6	Graphene	11.992	Northumbria Univ	UK	Shang, Mengmeng
7	Perovskite	10.645	Soochow Univ	Japan	Luo, Zhiyang
8	Phosphorescent OLED	10.552	Jilin Univ	Singapore	Yu, Xiaoguang
9	Perovskite solar cell	10.091	Hebei Univ	Germany	Haas, Harald
10	Eu3+ phosphor	9.91	Tsinghua Univ	France	Haigh, Paul Anthony

Table 4: The comparison of detected emerging concepts and research topics by four selected methods (E-score, LDA, TF-IDF and Term count) within Flash memory and LED research area

Flash Memory Technology				
Emerging concepts	**E-score**	**LDA**	**TF-IDF**	**Term count**
1	- Phase change random-access memory (PCRM)	- Phase change random-access memory (PCRM)	Novel material options for development of memory cells: Tetracyanoquinodimethane (TCNQ) , Nanocrystal based memory cell, SiNx, Fullerene	-
2	- Resistive random-access memory (RRAM, Memristors)	- Resistive random-access memory (RRAM, Memristors)	- Spin transfer torque memories	-
3		- Zinc-oxide charge trapping memory cell	- SONOS memory cell	-
4		- Graphene (for development of flash memory)		-
5		- Novel application area for flash memory in wireless sensor device		-
LED Technology				
Emerging concepts	**E-score**	**LDA**	**TF-IDF**	**Term count**
1	- Phosphorescent organic (OLED)	- Phosphorescent organic (OLED)	Novel material for enhancing LED performance: ZnTe, quinacridone, organoborn	-
2	- Graphene	- Graphene (appeared in topic 8)	Components: microball lens	-
3	- Visible light communication (VLC)	- Visible light communication (VLC) (appeared in topic 1)		-
4	- Organometal halide perovstike	- Novel material for LED fabrication: - ZnO, GaN (appeared in topic 8)		-



(a) Topic 1



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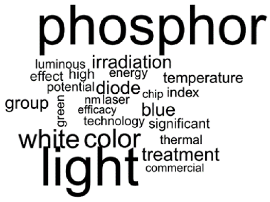

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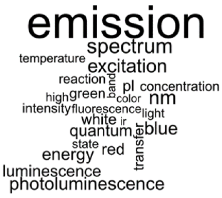

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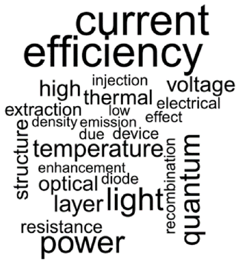

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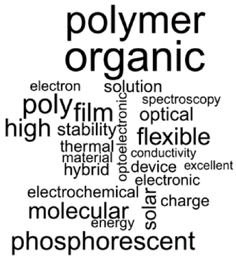

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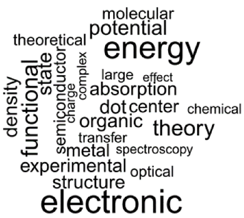
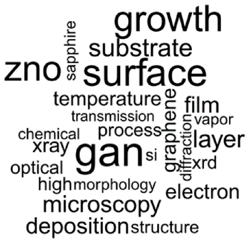


(g) Topic 7



(h) Topic 8

Fig. 3: Word clouds of eight topics created for LED technology using LDA.

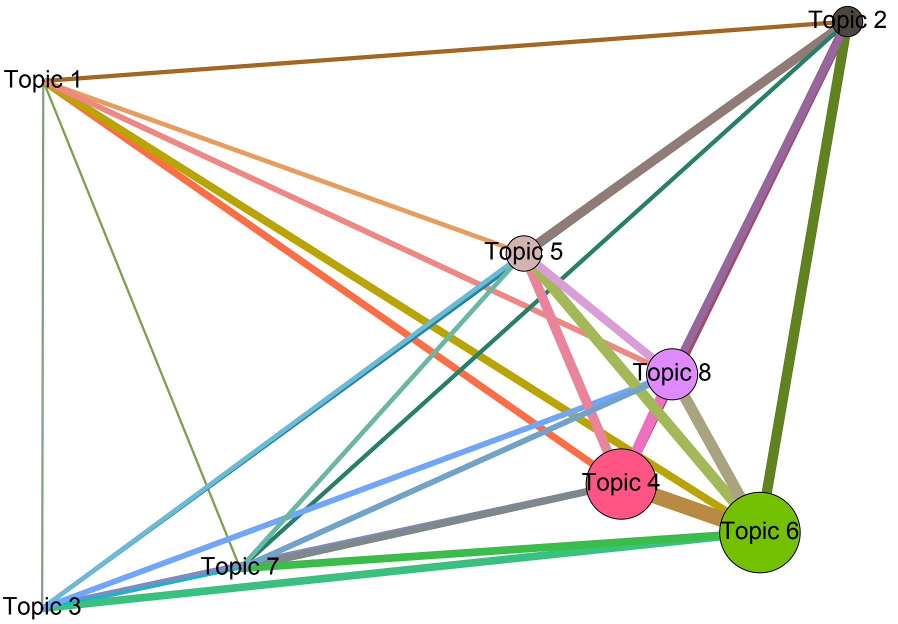


Fig. 4: Bipartite graph showing the relationship between the light-emitting diode (LED) topics. The graph consists of 56,985 nodes and 455,816 edges connecting the document nodes to topic nodes

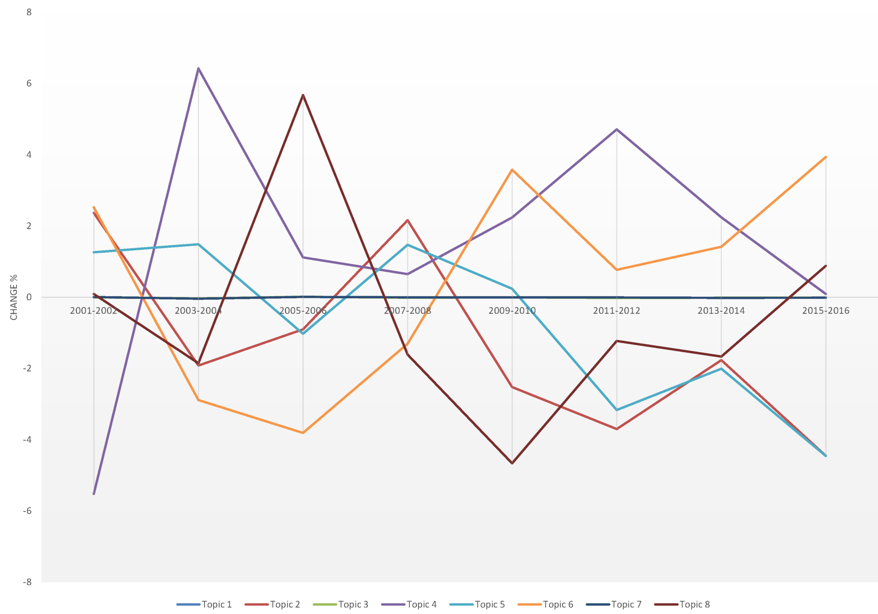
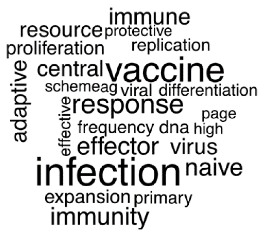


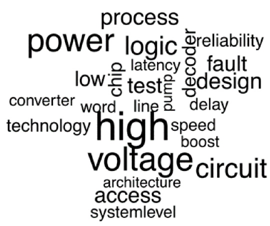
Fig. 5: Topical change of light-emitting diode (LED) technology, 2001-2016.



(a) Topic 1

(b) Topic 2

(c) Topic 3

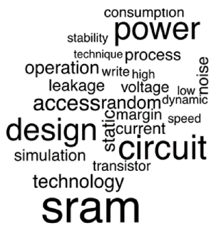


(d) Topic 4

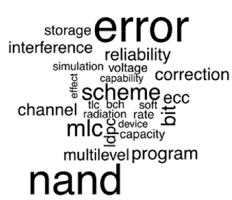
(e) Topic 5

(f) Topic 6

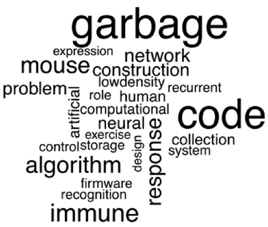
(g) Topic 7



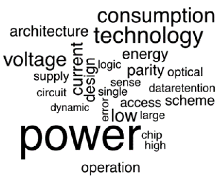
(h) Topic 8



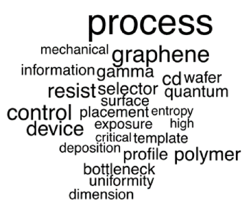
(i) Topic 9



(j) Topic 10

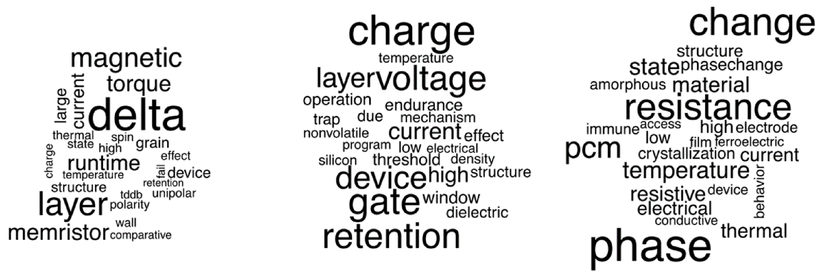


(k) Topic 11



(l) Topic 12

Fig. 6: Word clouds of 15 on flash memory topics created using LDA.Topic 1-12



(a) Topic 13 (b) Topic 14 (c) Topic 15

Fig. 7: Word clouds of 15 on flash memory topics created using LDA.Topic 13-15

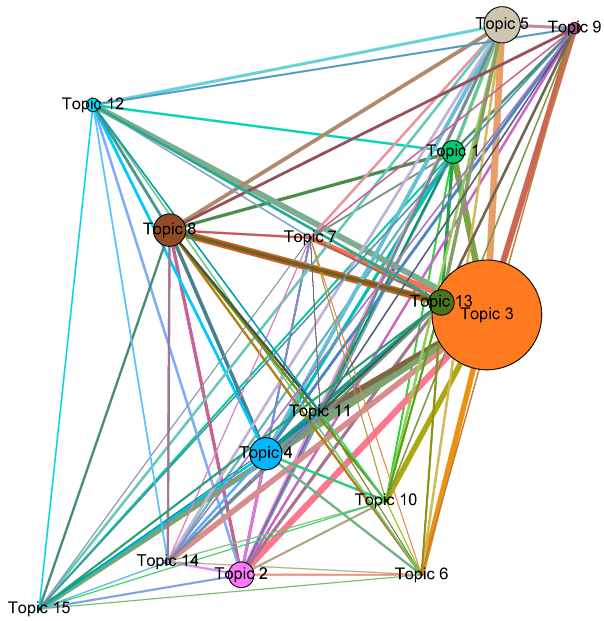


Fig. 8: Bipartite graph showing the relationships between the Flash memory topics. The graph consists of 10,734 nodes and 160,785 edges connecting document nodes to topic nodes.

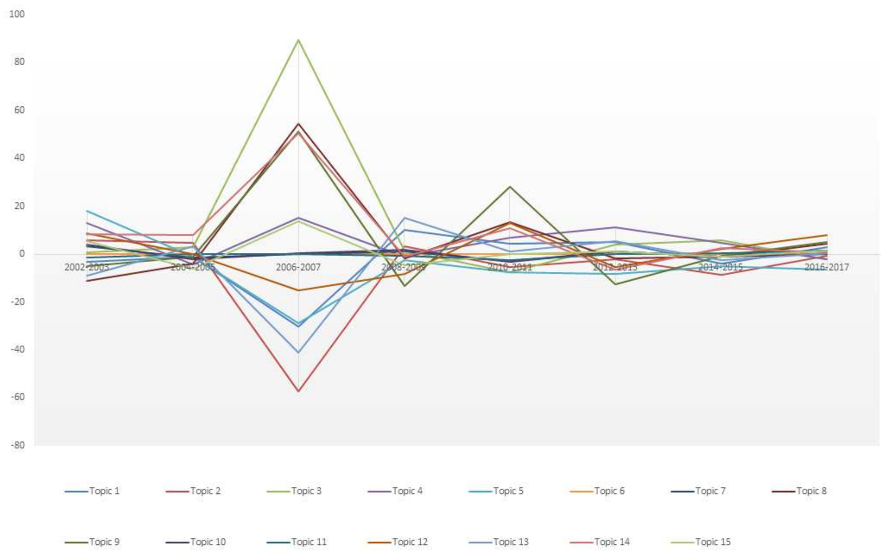


Fig. 9: Topical change of Flash memory technology, 2002-2017

Table 5: Ten highest delta values for LED using TF-IDF weights between year 2006 and 2016

	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
2006-2007	ageing (0.67)	carbazolyl (0.66)	dcjti (0.64)	tiox (0.64)	soil (0.62)	nano structured (0.61)	navigation (0.6)	week (0.6)	programming (0.6)	agau (0.59)
2007-2008	miso rientation (0.82)	chroma (0.69)	lcos (0.66)	quinacridone (0.66)	oxygen deficient (0.66)	znte (0.63)	alinn (0.61)	nonpolar (0.61)	cacl (0.6)	tone (0.6)
2008-2009	dibenzosilole (0.68)	inasn (0.66)	stamp (0.64)	qwip (0.63)	npss (0.62)	abcvth (0.61)	pbse (0.6)	term (0.6)	diffractive (0.59)	phenan throline (0.59)
2009-2010	organoboron (0.68)	cent (0.66)	code (0.64)	vcsels (0.64)	pscs (0.62)	balancing (0.61)	questionable (0.6)	surface textured (0.6)	cris (0.59)	laser induced (0.58)
2010-2011	fret (0.73)	greenish yellow (0.72)	gasb (0.71)	sigma (0.69)	mold (0.65)	phenoxazine based (0.63)	buffer (0.62)	auramine stained (0.61)	regulation (0.61)	sustainable (0.6)
2011-2012	caalphasialon (0.73)	bifurcation (0.72)	nand (0.69)	bccb (0.69)	mini (0.67)	void (0.65)	spinleds (0.65)	nuvleds (0.64)	ppfd (0.63)	andnboolean (0.63)
2012-2013	microball (0.68)	elution (0.67)	under water (0.67)	cscl (0.67)	prestrained (0.67)	pelectrode (0.64)	inventory (0.63)	electromer (0.63)	mgal (0.62)	indeno (0.61)
2013-2014	branched (0.74)	vshaped (0.7)	polycyclic (0.7)	yellow (0.68)	invar (0.68)	czts (0.67)	rhenium (0.66)	algaas (0.66)	traffic (0.65)	poly morphism (0.65)
2014-2015	chirped (0.76)	thiophene based (0.72)	tfled (0.71)	imin opyrrolyl (0.7)	dpvbi (0.67)	pppy (0.66)	stepdown (0.66)	benzoxazole (0.65)	fullcell (0.64)	peltier (0.63)
2015-2016	phen (0.71)	cbpo (0.68)	itoag (0.67)	nickel (0.65)	recl (0.65)	lifi (0.64)	cupc (0.63)	niau (0.62)	olets (0.59)	phycocyanin (0.58)

Table 6: Ten highest delta values for Flash memory using counts between year 2006 and 2016

	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
2006-2007	memory (786)	flash (400)	cell (317)	paper (178)	system (149)	technology (144)	performance (138)	device (135)	storage (127)	design (124)
2007-2008	memory (182)	cell (89)	flash (76)	energy (59)	read (57)	low (55)	nand (52)	structure (51)	simulation (50)	immune (43)
2008-2009	memory (552)	flash (352)	performance (179)	cell (177)	paper (138)	technology (123)	storage (111)	device (111)	write (101)	charge (99)
2009-2010	surface (21)	policy (19)	effector (18)	mouse (13)	ftl (12)	parallel (11)	overhead (11)	address (10)	mw (10)	protection (9)
2010-2011	memory (745)	flash (395)	cell (257)	device (162)	performance (141)	nand (117)	paper (114)	current (106)	layer (106)	storage (104)
2011-2012	cell (129)	gate (81)	paper (66)	process (57)	error (52)	retention (51)	high (49)	voltage (48)	nand (45)	sram (39)
2012-2013	performance (62)	power (57)	logic (54)	storage (44)	ssds (41)	flash (38)	cmos (38)	access (35)	scheme (34)	ssd (34)
2013-2014	memory (298)	cell (176)	paper (87)	performance (80)	sram (73)	access (72)	write (66)	magnetic (58)	ssd (56)	storage (55)
2014-2015	flash (92)	rate (63)	technique (58)	error (51)	performance (43)	data (43)	ecc (40)	disk (39)	write (37)	memristor (36)
2015-2016	memory (596)	cell (326)	flash (181)	performance (170)	read (143)	device (128)	resistive (125)	channel (117)	operation (116)	power (108)

Table 7: Ten highest delta values for LED using TF-IDF weights between year 2006 and 2016

	1th	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
2006-2007	hydrogen (0.52)	mev (0.49)	defective (0.41)	oxynitride (0.41)	tcnq (0.4)	tip (0.4)	xray (0.37)	trap (0.37)	onchip (0.35)	amorphization (0.35)
2007-2008	intermittent (0.63)	dipole (0.62)	lambda (0.51)	bch (0.5)	delta (0.5)	speech (0.49)	mlcs (0.48)	tcells (0.46)	cmol (0.44)	alloptical (0.44)
2008-2009	polymer (0.58)	movement (0.54)	vsasfg (0.53)	cobalt (0.52)	rtn (0.52)	multigate (0.52)	wsn (0.47)	health (0.47)	dfm (0.47)	laser (0.46)
2009-2010	memristor (0.61)	zro (0.6)	coefficient (0.54)	sttram (0.54)	register (0.51)	deployment (0.5)	pathogen (0.5)	mbus (0.49)	injection (0.49)	status (0.48)
2010-2011	amorphous crystalline (0.59)	tnf (0.56)	delta (0.54)	fea (0.52)	round (0.51)	swap (0.5)	victim (0.49)	mlc (0.48)	multilayer (0.47)	ti (0.46)
2011-2012	sb (0.65)	gamma (0.63)	fringe (0.61)	trim (0.6)	lcmv (0.56)	bidirectional (0.55)	call (0.55)	ptype (0.54)	pzt (0.53)	nano structure (0.53)
2012-2013	treg (0.72)	imd (0.7)	transaction (0.62)	nano laminate (0.6)	nucleations (0.58)	sneak (0.58)	nano crystalbased (0.56)	transgenic (0.55)	dcsf (0.54)	logger (0.54)
2013-2014	overlay (0.75)	ga (0.6)	unreliable (0.6)	coset (0.57)	sinx (0.55)	uv (0.54)	mobile (0.54)	nps (0.54)	seus (0.53)	fullerene (0.53)
2014-2015	nk (0.66)	fg (0.64)	backup (0.59)	sonos (0.57)	sorting (0.56)	sibased (0.55)	highrate (0.51)	cm (0.51)	approximate (0.51)	ncap (0.5)
2015-2016	stuckat (0.66)	sort (0.59)	uncertainty (0.58)	segment (0.58)	pico (0.57)	early (0.55)	video (0.55)	pwm (0.54)	spintronic (0.54)	tsv (0.54)

Table 8: Ten highest delta values for LED using counts between year 2006 and 2016

	1th	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
2006-2007	high (296)	light (290)	current (275)	efficiency (274)	leds (199)	optical (195)	quantum (191)	power (142)	method (141)	organic (140)
2007-2008	light (385)	emission (262)	leds (245)	organic (223)	efficiency (198)	lightemitting (176)	surface (163)	spectrum (158)	high (146)	energy (144)
2008-2009	temperature (146)	structure (130)	phosphor (122)	emission (114)	polym (92)	excitation (91)	design (82)	transition (80)	applied (79)	physics (78)
2009-2010	light (336)	high (255)	phosphor (163)	layer (159)	organic (158)	optical (157)	leds (123)	current (122)	efficiency (120)	device (118)
2010-2011	light (534)	efficiency (342)	emission (325)	high (255)	energy (235)	blue (229)	spectrum (223)	method (221)	electron (203)	surface (194)
2011-2012	light (312)	optical (283)	power (245)	high (241)	efficiency (224)	emission (204)	leds (203)	temperature (191)	phosphor (190)	graphene (189)
2012-2013	light (407)	leds (307)	lightemitting (252)	high (221)	layer (217)	publishing (216)	energy (199)	diode (197)	method (182)	phosphor (175)
2013-2014	emission (416)	energy (331)	light (315)	blue (254)	device (214)	electron (182)	group (178)	phosphor (170)	structure (169)	potential (165)
2014-2015	performance (315)	fluorescence (252)	quantum (244)	high (223)	emission (200)	blue (191)	color (159)	flexible (157)	molecular (141)	study (141)
2015-2016	inactivation (13)	milk (11)	fabryperot (10)	ledpdt (9)	dinuclear (9)	persulfate (8)	agzn (8)	photoinduced (7)	guided (7)	tcta (7)