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Exploring the fundamential conceptual units of technical emergence

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***Abstract*—The study of emerging technologies is broad and has multiple and often poorly integrated threads. For example, some literature draw from a number of characteristics such as radicalness, growth speed, coherence, impact, uncertainty and ambiguity while other only look at expected economic benefits. This fractured view of the growth of new technologies has created a hodgepodge of approaches and a dearth of fundamental measures within this research space. Recent efforts at developing a more fundamental measure of technological behavior have yielded "Technical Emergence" - a simple proposition which seeks to measure the growth of concepts within a community of users by tracking Novelty, Persistence, Community and Growth. This fundamental unit induces the possibility to actually measure and, more importantly test, its behavior using repeatable bibliometric techniques. We discuss in detail the conceptual origins and evaluate the concept of technological emergence and relations of indicators to it.**

I. Introduction

Rotolo, Hicks and Martin [1], in a recent literature review, made an effort to define what is emerging technology. The authors highlighted the multiple domains of research where the concept of emerging technology has been used, such as science and technology policy, management, economics, and scientometrics. Partly due to the large number of domains that have adopted the concept, the amount viewpoints towards technological emergence are extensive. For example, [2] and [3] take a science policy view to emergence and focus on the economic influence and impact on competition. In the author's work, economic impacts are viewed on a macro-level and similar to Martin [4] who view emerging technology as a macro level process where a novel technology with broad economic and/or societal impacts emerges. Marketing and management view on emergence draws from the technological adoption literature. For example, [5] looks at emergence through a marketing view uncovering the impacts of network externalities in emerging technology markets. A micro level vantagepoint to emergence is also offered by [6], who looks at the dynamics of companies in adopting new technologies to their portfolio. There is also extensive literature connecting emerging technologies to the innovation management literature, such as [7].

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The challenge in the current emerging technology literature is that it creates a fractured view of the growth of new technologies, having created a hodgepodge of approaches and a dearth of fundamental measures within this research space. Theoretically framed papers have gone to draw from a number of characteristics, such as radicalness, growth speed, coherence, impact, uncertainty and ambiguity, in trying to capture the theoretical concept of emergence. Much of this effort remains detached or overlays existing theoretical concepts such as evolutionary theory of technological change, disruptive innovation, radical innovation or invention, as seen from the working definitions of the IARPA FUSE project presented in Fig.1.

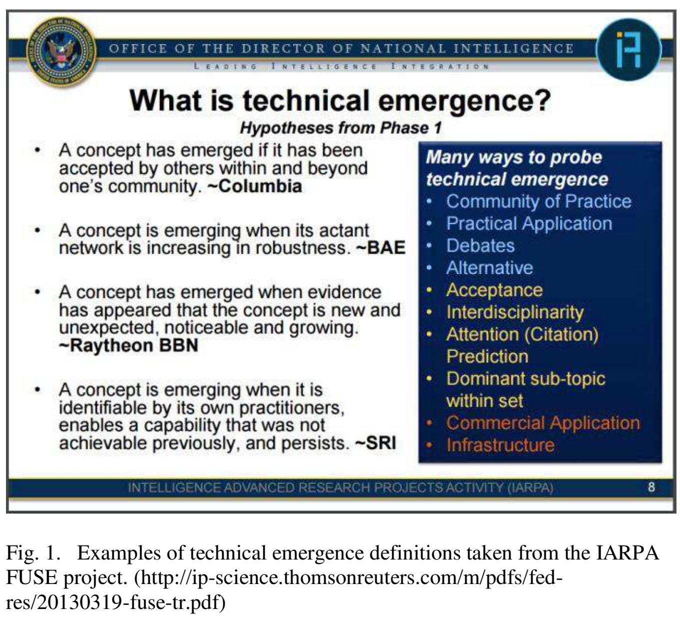

Fig. 1. Examples of technical emergence definitions taken from the IARPA FUSE project. (http://ip-science.thomsonreuters.com/m/pdfs/fed-res/20130319-fuse-tr.pdf)

This paper views emerging technology as an operational construct, drawing from the technological forecasting discussion. We review, in short, the theoretical and operational background of technological emergence. Then we move to describe several practical measures of emergence that in parts all answer to different characteristics of emergence. Finally, we discuss in detail the conceptual origins and assess the concept of technological emergence as both a theoretical and operational construct. In addition, we focus our discussion on the relations of different indicators to the emergence concept.

The paper is structured as follows. The following section will go through a portion of the relevant background literature. Section III will review practical measures of technological emergence. The remaining two sections discuss and conclude the paper.

II. Backgroung

A. *Theoretical views to technological emergence*

Our fascination with technological emergence is long-standing. Wells [8], already in 1902, argued that by approaching the implications of new technologies in a systematic manner would enable a better society. The foundations of systematic analysis of technological change stem from the Technological Forecasting (TF) tradition. This field of science has had a strong policy focus from early on, having the methodological and theoretical foundation of TF created after the Second World War in organizations such as the RAND Corporation. Authors such as Herman Kahn [9], later noted as the "father" of scenario analysis, Dalkey, Helmer and Rescher [10] on Delphi method and Ayres [11] on technological forecasting, created the basis for what is known as TF today.

This systematic approach to analyzing the potential of technology has grown to large-scale analysis processes operationalizing technological emergence, trajectories and impacts. A large portion of this effort is macro-level studies (e.g. United Kingdom and Japan), focused on creating a large national level technology plan. Effort in the US, not as focused on a national level plan, focuses more on efforts done in individual organizations [12].

Regardless of the objectives setting of different regions, TF is a systematic approach to analyzing technological futures. From a theoretical perspective, TF could be seen as having two traditions, one focusing on forecasting and the other on foresight. The main difference between the before mentioned is that forecasting takes a passive role to technology while the foresight tradition assumes that the future is created [13]. Foresight works through a theoretical frame where the future is ex ante conceptualized through the anticipatory futures or scenarios framework. The operational elements are mostly qualitative in nature. In contrast, forecasting relies on the theoretical framework of technological progression and linearity of innovation, operationalizing development through a quantitative process.

Overall, TF remains as a pool of methodological approaches rather than a rigorous theory. Theoretically, TF is linked to the discussion on technological change and theories such as the evolutionary theory of technological change (ETTC) [14]. For example, ETTC offers one robust, but controversial, theoretical construct to understanding how technologies emerge and develop. Rooted in the Darwinian model of evolution in biological system, ETTC extends the concept of evolution to the complex-system of technological development. This is done in parts by using an analogy of biological evolution in the technological context, but also looking at technology as a part of the biological evolution.

A key aspect of this evolutionary process is to understand the introduction of novelties that impact the status-quo of the system. In ETTC, technology is viewed as improvement through intelligent means, which allows for intentionality and simply random processes. In this process of improvement, we easily understand how selection processes explain to survival of the fittest, "...but it cannot explain the arrival of the fittest"[15]. Arrival, or emergence as we would rather call it, is a term used to defined "the arising of novel and coherent structures, patterns, and properties during the process of self-organization in complex systems"[16]. Goldstein explains the construct of emergence as a nonlinear interactivity in a complex system that leads to novel and unexpected outcomes. By unexpected Goldstein refers to outcomes that are not easily understood as the sum of parts embedded in the novelty.

B. *Operational construct of technological emergence*

To create an operational construct of technological emergence we strive toward a proxy measure of the arrival of the fittest. In the tradition of foresight, the operationalization strives to an ex ante evaluation of emergence, whereas the forecasting tradition focuses on the ex post - that is the rapid identification and analysis of progression of the emergent.

Literature argues that emergence has five characteristics; ostensivity, global presence, coherence, dynamism and novelty. Emergent phenomena has undoubtedly the challenge of not being easily predicted or deduced from the parts of that make the whole, rather we are reliant on emergent being recognized by showing themselves. This ostensivety is one of the key aspects of emergence, a clear challenge for both ex post or ex ante evaluation of emergence. Ostensivity is a natural consequence of emergents being both novel and result of a dynamic process in a complex system. Even if we are able to identify the parts of the whole, and model the processes of the system to significant extent, it is challenging to forecast the novelty prior to it appearing. Emergence also requires that the observation occurs on a macro level, rather than in the confines of any micro level social structure. Although have a well-founded critique on the requirement of globality of the emergent [17]. We also assume emergents to be coherent. This means that the emergent, post arrival, is to some extent stable allowing the system to understand the emergent and its survival in the system.

In a short communication [18] made an effort to show operationalizations of Goldstein's [16] characteristics. In the paper, the efforts to map science are seen as a tool operationalizes ostensive properties of emergents. The justification here is, that by creating explicit visuals of science emergents would make themselves recognizable earlier. The global and macro level of an emergent is then identified through extending the mapping of scientific specialties. Templeton and Fleischmann [18] continue to propose that the global and macro level of an emergent field is operationalized in a similar manner through maps of science focusing on research specialties[19]. This seems as an underdeveloped operationalization, as the emergent behavior and its globality is more evident through a processes of diffusion of the emergent topic through regional, social and or disciplinary boundaries. An example could be modeling the dynamics and reach, the co-evolution, of a field through number of researchers, organization, cities or countries [20] taking part in the field.

Coherence of the emergent is operationalized with the long tradition of scientometrics co-citation analysis [21] and co-word analysis [22]. This analysis should, probably, also include bibliographical coupling [23]. As Templeton and Fleischmann [18] understand, dynamism of the emergent is the increase of entities over time [24], or the emergence of a large connected component in a co-authorship network [25], [26] what is dynamism.

Finally Templeton and Fleischmann [18] look at novelty, through bibliometric methods in specialty detection [27], information foraging [28], citation bursts [29], and interdisciplinarity of citations [30].

III. Practical Measure

A. *Finding the simplest feature*

A common theme across many of the effort noted above is a reliance on bibliographic data and, in many cases, citation data. The first of these represents an obvious path of research since bibliographic data provide a ready source of scientific information covering long time spans. Using bibliographic data negates the need for more time consuming and limited techniques such as case studies and allows for repeatability in testing results.

The second is more problematic since citation data is limited to a small set of scientific databases (primarily Web of Science and SCOPUS). This limitation is an issue when analyzing activity outside of core science areas covered the journals indexed in these two data sources [31]. Gaps include patent data which, although contain citation data, do not necessarily behave in a manner consistent with the science-based citations [32]. Citation data also introduces a time lag into the emergence analysis in that up to five years is required for articles to collect significant citation activity [33].

Given the issues of time lag and availability of citation data and seeking the broadest applicable measure of technical emergence, other features must be considered. One basic feature available across almost all data sources is the noun phrase. This feature is readily extracted using natural language processing techniques and can be refined using other techniques such as fuzzy matching and lemmatization. In addition to Natural Language Processing, Topic Modeling can also be used to extract unigrams which can be folded into phrases. The authors discuss the relative merits of these two approaches elsewhere. [34].

B. *The components of technical emergence*

Given the Noun Phrase as the base feature for technical emergence, the next challenge is to select which elements of the various definitions of technical emergence are compatible with the base feature. The principle challenge is one of operationalization. Several aspects of technical emergence considered by the research community are intriguing but extremely difficult to operationalize. Tracking debates is possible but requires full text records [35]. Tracking commercial application is also feasible but success varies depending on technical domain. Through trial and error, combined with our experiences during the FUSE program, and after experimenting with several different operationalizations, we found that four components of Technical Emergence work extremely well with the noun phrase base feature. These four components are: Novelty, Persistence, Community and Growth.

Novelty, with some exceptions, is relatively easy to identify in bibliographic data by comparing time slices of the data to one another. In its simplest form, novelty detection is operationalized by the emergence of a new term. For example, in [36] novelty of ideas is mapped through the introduction of new terms. In the study the authors focused specifically in the introduction of new keywords, but a similar analysis can be easily extended to abstracts or even full-text of a patent or publications. However, this simplification of novelty, while factual, might turn out to be an oversimplification. In a more practical solution, the emergent term is expected to have attributes such as use by multiple actors, duration of use or volume of usage, defined by persistence below. Some issues arise when phrases reduce to abbreviations or acronyms. Synonyms are also a potential issue. However, both of these challenges can be mitigated, but not eliminated, using machine learning techniques.

Persistence is a bit more problematic. The principle issue here is the possible presence of the hype cycle [37]. If present, there are bibliometric techniques to identify and mitigate its impact [38]. An approach to persistence is presented in [39] where topics, or threads as described by the authors, are tracked though birth to death. The paper exemplifies how emergent can be seen as threads which have a life-cycle, and only the existence of such creates a novel topic. Ultimately, the use of a persistence measure impacts our ability to push emergence identification back to inception. However the measure is necessary to capture aspects of coherence which ultimately limit how early one can spot an emerging term. Persistence is used instead of coherence because it is much simpler to measure and can potentially form before coherence.

Community is key in the process of emergence, would we model it as purely a volume distribution [40] or as a network of actors [41]. However, operationalizing a community is one of most challenging components in that it requires tracking the feature in the context of other features. Names of people and/or organizations must be folded into the equation to determine community. On an operational level, this does present some issues. One could just track the number of different names associated with a noun phrase or a technology dataset at given points in time [36], [42]. In a narrowly focused technological case, such as [42], the factor of community building can be easily quantified by author identification, co-authorship networks and by linking human resources to organization structure. However the true complexity of teams creates problems. Ideally one would want to track the adoption and use of noun phrase by other researchers who are not directly associated with the team that minted the new concept. However, to do this one must assess how sets of authors are connected. If a researcher coins a phrase and that phrase is used by post docs and graduates students associated or funded by the source of the new phrase is has less potential impact than the use of the new phrase by someone less directly associated with the source who might have picked up the phrase at a conference or from an article. These issues are not insurmountable but they do require attention during implementation.

Growth data, like novelty, is relatively easy to collect but the difficulty rests in what to do with the raw data. After extracting the feature and collecting its frequency of use over time there are several different paths one could take with the data. One route is to use logistics curves to assess growth [38], [43], [44]. This forecasted based approach is attractive because it lends itself to modeling and provides a basis for future forecasting of emergence. Using the logistic growth curve with the emergence data we have is not without problems. Even though there is a plethora of models available [43], many of these fall short in being capable of producing forecasts that would be practical or at least give the researchers too much freedom to manipulate the end result [45]. There are other approaches as well such the probabilistic models. These models go beyond the simple logistic curve, most often extending an unsupervised approach to produce a topic, term or concept that emerges. In a simple form, existing models such as Latent Dirichlet Allocation can be used to track the time series of latent semantic patterns [46] and to forecast these to the future [47]. A more practical solutions would require creating or adapting an existing model to this specific task [48]. The key element is to fit the growth data into a model that produces a sense of state of emergence and perhaps some insight into future trajectories.

Combined, these four component represent a tractable measure of technical emergence operationalized using a variety of bibliographic data that can produce repeatable, testable results. The components presented should be seen as factors, rather than operationalizations. The factors create the conceptual frame of how to understand emergence, its evolution and building of an ecosystem around the technology, in line with the evolutionary theory on technological change [14].

TABLE I. FACTORS AND EXAMPLES OPERATIONALIZATIONS OF EMERGENCE

Factor	Operationalizations
Novelty	term identification[49], term clusters[50]
Persistence	Topic Detection and Tracking (DARPA TDT) [51]
Community	Volume based models [40], research networks [52]
Growth	Fisher-pry, Gompertz etc. [43] probabilistic approaches [48]

Table I shows a non-exhaustive list of operationalizations for different factors of technological emergence. This highlights the fact that with existing operationalizations, or with novel ones, the question is if the proxy measure serves as explanatory variable to the conceptual factor. As import is the fact that none of the factors on their own gives a holistic explanation of emergence and that technological emergence is and should be understood as an evolving system[14].

IV. DISCUSSION AND CONCLUSIONS

Technology Forecasting is clearly more methodologically oriented than drawing from a strong theoretical foundation. Early [11] or more recent [38], [53] studies on Technology Forecasting are heavily reliant on describing methods of forecasting rather than laying an foundations to understand its theory. Studies on technological change [54] and its evolutionary aspect [14] as well as more recent work trying to capture the content of emergence [1], [16] are putting forward a foundation to a holistic view on emergence. We suggest, that technological emergence is founded on four factors, novelty, persistency, community and growth – all of which are equally important in creating a understanding on if something is emergent. We are skeptical if we should incorporate factors such as global or macro-scale, as emergent are also present in niche and localized spaces [55].

Although the presented analysis approach represents a technically feasible approach to capturing technical emergence it is far from perfect. The approach does not necessarily capture all the dimensions of technical emergence. Noun phrases that reuse or re-defining older terms can cause problems. Technical areas which use “common” terms to describe complex ideas can cause issues (e.g. “center of gravity”). The approach is not cross lingual. The absence of a counterfactual is problematic – terms are emergent or not showing emergence. In other words, this approach cannot differentiate between good ideas and bad ideas.

However, despite these limitations, this approach does have the advantage that it can be run repeatedly on a variety of scientific and technical data with minimal effort. The result can be robustly tested by analyzing older data and comparing the result to current data. Planned future efforts involve just this kind of test and evaluation protocol. A study of twenty years of nanotechnology publications is in the early phases of development. Other studies will follow. Our hope is that ability to easily empirically test and evaluate results will open a new avenue in the study of technical emergence that could potentially provide new insight into the innovation process.

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