An empirically informed taxonomy for the Maker Movement

Christian Voigt[1], Calkin Suero Montero[2], Massimo Menichinelli[3,4]

[1] Zentrum für Soziale Innovation, Technology and Knowledge, Vienna, Austria
voigt@zsi.at
[2] University of Eastern Finland
calkin.montero@uef.fi
[3] IAAC | Fab Lab Barcelona, Barcelona, Spain
massimo@fablabbcn.org
[4]Aalto University, School of Art, Design and Architecture
Media Lab Helsinki, Helsinki, Finland
massimo.menichinelli@aalto.fi

Abstract. The Maker Movement emerged from a renewed interest in the physical side of innovation following the dot-com bubble and the rise of the participatory Web 2.0 and the decreasing costs of many digital fabrication technologies. Classifying concepts, i.e. building taxonomies, is a fundamental practice when developing a topic of interest into a research field. Taking advantage of the growth of the Social Web and participation platforms, this paper suggests a multidisciplinary analysis of communications and online behaviors related to the Maker community in order to develop a taxonomy informed by current practices and ongoing discussions. We analyze a number of sources such as Twitter, Wikipedia and Google Trends, applying co-word analysis, trend visualizations and emotional analysis. Whereas co-words and trends extract structural characteristics of the movement, emotional analysis is non-topical, extracting emotional interpretations.

Keywords. Maker Movement · Internet Science · Taxonomy Development · Co-word Analysis · Clustering · Emotion Profiling

1 Introduction

Taxonomies are central elements to support the conceptual, methodological and scientific exploration of emerging phenomena such as making and the Maker Movement. The Maker Movement emerged from a renewed interest in the physical side of innovation following the dot-com bubble, the rise of the participatory Web 2.0, the diffusion of Open Source and the decreasing costs of many digital fabrication technologies. Simultaneously, the renowned publication venues Make magazine was launched in 2005 [1]. Neil Gershenfeld [2] calls the Maker Movement the next digital revolution as it enables personal fabrication on people's desks. The Massachusetts Institute of Technology's 'Bits to Atoms' program, which dates back to 2001, is often quoted as the first step of the Maker Movement. Open source and Web 2.0 did not only democratize knowledge production but also the means of design and invention by 'industrializing the Do It Yourself (DIY) spirit' [3]. Today rapid prototyping is more accessible than ever before due to affordable computer-aided design software, 3-D printing, laser cutting and a knowledge community that is pushing the limits of what can be produced by individuals. For example, sales of goods on ETSY, an e-commerce marketplace specializing in crafts and maker products, reached a turnover of about 2.4 billion USD in 2015 [4].

Yet, it should be fair to say that the Maker Movement is primarily practice oriented, characterized in large parts by tacit knowledge and heuristics obtained through a continuous, problem-driven exchange within maker communities. However, in order to obtain a more robust and consolidated framework for analyzing the Maker Movement we argue that it is important to capture and systematize existing key concepts, semantic differences and changing connotations depending on geographical regions to advance and focus future research efforts.

In this context we look at the possibilities of Internet science as a field of research poised to support taxonomic developments. The authors of this paper aim for an explicitly interdisciplinary approach, combing the expertise of digital social innovation, digital fabrication and Natural Language Processing (NLP). This combination of diverse research domains is meant to strengthen the final taxonomy's pragmatic value as well as methodological efficiency in producing the taxonomy, a non-trivial challenge considering the epistemological differences inherent to interdisciplinarity [5].

Hence, our contribution to Internet science is a) to open the discussion in order to create a common understanding of terms and related implications; b) to suggest a first taxonomic structure for the Maker Movement (people, places and activities); and c) to explore the relevance and explanatory usefulness of social media in creating context.

This paper is organized as follows. First, we outline the benefits of pursuing a taxonomy of the Maker Movement. We then describe our methodology supporting the overall development of the taxonomy as well as specific data collection procedures (section 3). In the fourth section we introduce some first basic components of a taxonomy around the Maker Movement, i.e. concepts related to Maker communities, spaces and activities. These concepts are then explored with the help of social media analysis (tweet mining) and access statistics (Wikipedia consultations, Goggle trends, related searches). This section also includes non-topical text analysis, extracting emotional interpretations from tweets. Here the aim is to enrich the meaning making process, exploring the possibility of attaching indications of joy or frustrations to Maker concepts, which can then be explored in more depth. The paper closes with a discussion of findings and an outline of next steps.

2 Why having a taxonomy discussion?

Classifying concepts, i.e. building a taxonomy, is a fundamental practice when developing a topic of interest into a research field. For our purpose we are going to distinguish typologies and taxonomies, the former being deductive assignments into a priori defined groups (ideal types) whereas the latter are inductively determined memberships of a posteriori identified categories [6]. Put differently, *typologies* are intuitive classifications, which might turn out to be exhaustive or too restrictive. *Taxonomies*, on the other hand, start empirically, focusing on categorizing cases based on similarities between observed variables [7].

Our taxonomy discussion is embedded within the European funded H2020 research project 'MAKE-IT', exploring maker communities and their links with Collective Awareness Platforms for Sustainability and Social Innovation (CAPS). CAPS serve to raise awareness of problems related to sustainability or social injustice, with the aim that communities can develop solutions collaboratively and share the required design and implementation efforts among many. Typically, forms of communication, coordination, guiding ideologies within maker communities etc. depend on their histories and organizational setting. For example, in open source communities we know that collaboration is guided by fairly powerful community norms [8], e.g. deciding when forking an open source project is permissible or how to peer review and bug fix open source code. Hence, a taxonomy is a useful instrument to discuss the broad variety of community related phenomena in a systematic way and keeping it accessible for all participants.

Understanding changing meanings. An on-going observation of how concepts are used over time often reflects the development of a field as knowledge becomes increasingly more specific. An example shown in section 4.2 refers to the relatively recent increase of 'maker spaces' as a search term, which became popular in 2011. We would assume that spaces dedicated to making existed before, but were simply subsumed under the concept of 'hacker spaces'. In fact, one of the early Hackerspaces, 'c-base' opened in Berlin in 1995, designing robotic devices that crossed the boundaries between the physical and the digital world [9].

Making research replicable and insights comparable. A further benefit of a taxonomy is that it provides some measure of unity to the description of research findings, which enables others to reconstruct and replicate the conditions under which a given method or procedure has been successful. Of course, this requires the taxonomy to be close to reality so that practitioners as well as researchers accept the taxonomy as a valid reflection of their experiences [10].

Working towards predictive and more general knowledge. A clear terminology is usually a sign of an established research area, where there is a sufficiently large body of knowledge describing the boundaries of a term and interdependencies between terms [11]. Hence, a common language will be a necessary precondition to better describe developments around the maker community in a European context, where earlier studies have already shown distinct characteristics between maker spaces and fab labs in terms of their network structures and interaction intensities [12].

3 A methodology for taxonomy refinement

A taxonomy cannot be created with one swift move. The long-term goal is to start with a draft, which is progressively unified and becomes an increasingly accepted terminology that precedes comparable and eventually generalizable knowledge [7]. Working towards this taxonomy will comprise multiple stages (cf. Figure 1, based on [11]).

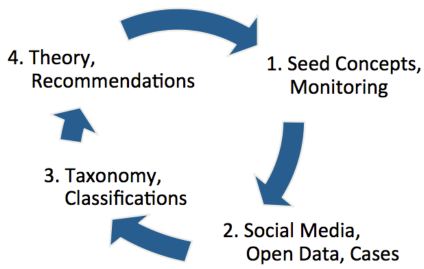

Fig. 1. Circle of taxonomy refinement

Since no new taxonomy can be created ex nihilo, we start with seed categories (*people*, *spaces* and *activities*) and seed concepts drawn from the existing literature (step1 1). In step 2, we monitor and explore available open and social media data in combination with observations and surveys from European maker communities. Aggregating multiple data explorations and experiences across multiple case studies will then allow us to draft a first version of the taxonomy, which is then published on the Web for further commenting (step 3). Eventually, some taxonomy entries can be linked with results from relevant research studies, for example concerning governance or value creation in maker spaces (step 4).

Seed categories and concepts. We found the combination of *people*, *spaces* and *activities* to be a recurring theme in many publications [13–15]. Although not all authors were using exactly the same labels and might refer to communities instead of people, or they focused on tools rather than the spaces, where people got access to the tools. The main purpose of working with these three areas was to have a first set of keywords, which could eventually lead us to related concepts. In this situation the exact naming is not overly relevant as long as the chosen seed concepts are broad enough and concepts within maker-related texts are sufficiently linked. A similar approach can be found when using folksonomies. A 'folksonomy' is a combination of the words 'folk' and 'taxonomy' and refers to the user-generated nature of a taxonomy based on social tagging, the public labeling or categorization of online recourses [16]. Folksonomies are likely to have flatter hierarchies than their scientific counterparts and have shown to converge towards smaller sets of frequently used tags, despite their decentralized and informal usage. The initial set of *seed concepts* used for exploring open and social media around the Maker Movement is as follows:

- *people*: maker, hacker;
- *places*: makerspaces, hackerspaces, fablabs;
- *activities*: DIY, 3d-printing, making, hacking, maker_education.

Not all concepts are equally useful as seed concepts due to their homonymic characteristics, e.g. you can hack into a computer, or hack a piece of wood. Even if the meaning stays the same, sometimes a word is used in a context that makes it less relevant for the intended analysis. For example, the DIY philosophy is said to define the

Maker Movement [17], when the same term is also frequently used with wedding preparations.

Taxonomic structures. Once a taxonomy has an *empirical basis* - as in biological classifications -, hierarchies are build around central categories which branch out into sub-categories [7]. In a 'Maker Movement' context, that could concern additive making technologies which include different 3D printing technologies such as Stereolithography (SLA), Digital Light Processing (DLP), Fused deposition modelling (FDM) , Selective Laser Sintering (SLS) etc. The same thinking could be applied to an activity such as 'maker education', here a first level differentiation might include the use of maker technology in formal, non-formal and informal education [18] and even further differentiation might then distinguish between electronic and fabrication kits, which enable different types of learning [19].

4 Experimenting with categories and seed concepts

Before we could start experimenting with seed concepts, we explored a number of data sources. Main criteria were open access and a minimum of limitations for analyzing data going back in time, so that conceptual changes could be identified. Sources meeting these criteria included Twitter, Wikipedia, Google Trends, The Guardian (a UK newspaper with an open API) as well as a number of bibliographic databases including Scopus [20] and Web of Science [21]. The list is by no means complete and other sources such as Google Scholar can also be accessed through web scraping, see [22] for a comparison of different citation databases.

The experimentations described in this section reflects stage two 'social media and open data analysis' of our overall methodology (cf. Fig.1) and aims at extracting related concepts as well as trending concepts. An additional experiment looks into the emotional profiling of groups of tweets, exploring the possibility of identifying concept related feelings such as 'joy' or 'frustration'.

4.1 Concept identification: Tweet mining and Google's related searches

Classification is key to conceptualizing a domain space, compare data, reason with data etc. As stated in section 2, classification can be done through a typology or a taxonomy [7]. The former relies on classifying along theoretical dimensions (e.g. a makerspace might be for-profit or non-profit), and the latter relies on empirical observations leading to measurable similarities. Different cluster techniques can then group similar concepts [23].

Tweet mining. In this section we start with selecting tweets containing hashtags commonly describing people, places and activities in and around the Maker Movement. From that corpus we started extracting frequent co-words (i.e. words co-occurring with specified hashtags). Co-words can be used as indicators of a concept's cognitive structure, and changes in co-words may indicate a change of strategy in order to make a concept more appealing or successful [24, 25]. The amount of tweets that can be accessed on one day is limited to 13,000 and includes tweets no older than the last seven days. This relatively small window of analysis means that events in that week can have a strong impact on co-word appearances, as we will see in the case of #makerspace tweets. We used different R packages [26] for accessing tweets [27], data clean up and generation of co-word matrices [28] and visualization [29]. For data cleaning, we removed English stop words, but avoided stemming in order to maintain readability of concepts. We did some lightweight curating of the resulting tables of frequent co-words by removing the plural or a different spelling of the seed concept. We analyzed a total of 50,097 tweets: 12,180 for #makerspace, 1,614 for #FabLab, 4,370 for #makerEd (a prominent hashtag for making in education), 13,000 for #3dprinting, 11,269 for #hacker and 7,664 for #maker.

#makerspace. We collected the tweets early November, when two education conferences took place, which also focused on the question 'How to apply maker concepts to education?' Firstly, the 2015 California STEM Symposium, a gathering of 3,100 teachers and administrators looking into how robotics or 3D-printing could increase the attractiveness of science, technology, engineering and math [30]. Secondly, the 17th conference of the American Association of School Librarians, thematizing the use of libraries as makerspaces [31]. Consequently Figure 2 showcases makerspaces with a focus on education, i.e. more than 2,200 tweets referred to #makerspace and to library, STEM or school.

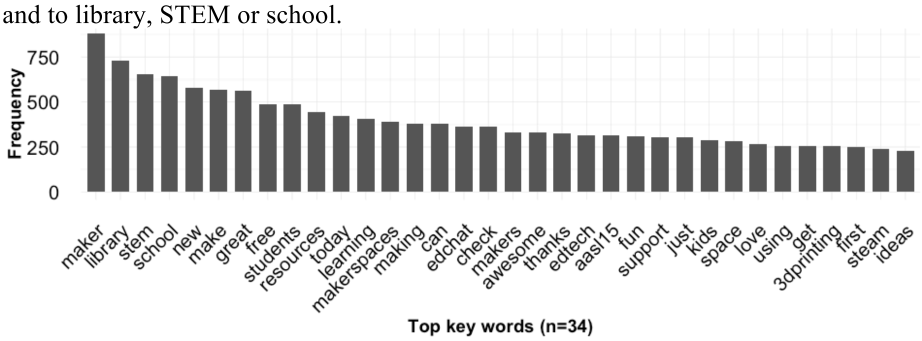

Fig. 2. Co-word analysis based on 12,180 tweets containing #makerspace (Nov 2015)

#makered. If we look at tweets explicitly referring to making in education, using the *#makered* hashtag, the term 'makerspace' appears first, confirming the high co-occurrence of both terms (Fig. 3).

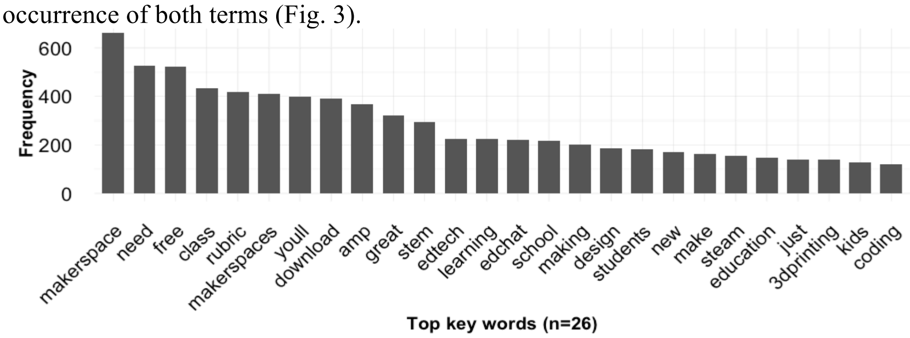

Fig. 3. Co-word analysis based on 4,370 tweets containing #MakerEd (Nov 2015)

However, the reminder of the co-word list looks quite differently indicating things like 'class', 'rubrics' and 'educational technology' (hashtag *#MakerEd*).

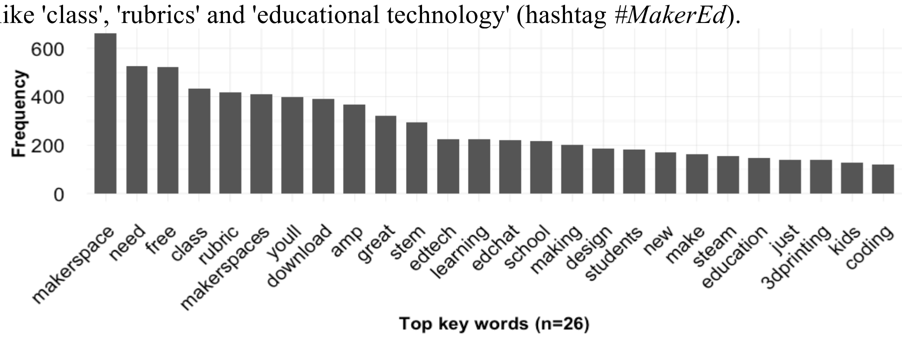

Fig. 4. Co-word analysis based on 4,370 tweets containing #MakerEd (Nov 2015)

In this context we can infer elements of a 'making in education' discussion around the need for assessing learners maker qualities in the setting of a class and, with less frequency, concrete activities such as coding and 3D-printing.

#3dprinting. If we follow up on #3D-printing, the educational dimension almost disappears. Rather, what we see are structural elements of the 3D-printing process, including parts, design, 3D-printers and filaments (see Fig. 5). Additionally the co-word list indicates discussion around novel uses of 3D-prinitng for the production of human tissue and body parts. Again, the co-word list shows the impact of a highly visible event during the week of tweet collection, when toy maker Mattel announced ThingMaker, a low cost 3D-Printer for kids at around 300 USD [32].

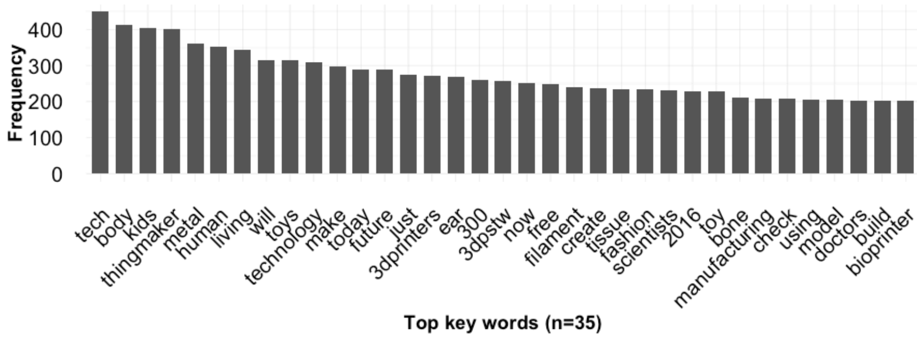

Fig. 5. Co-word analysis based on 13,000 tweets containing #3dprinting (Feb 2016)

A further dataset of 1,614 #fablab related tweets was manually filtered, since a single message (the opening of a FabLab in India) was retweeted 104 times (6.4%) and dominated the co-word analysis. Although the retweets were certainly relevant, they were also very specific in a geographical sense. Comparing co-word rankings from 'makerspace' tweets (see Figure 2) with 'FabLab' tweets, the former showed more educational key words, whereas the latter had more entrepreneurial tendencies. However, at this stage our focus is on getting a first impression of whether or not the presented analyses can generate some early hypotheses, which we can then revisit with larger data sets covering a span of several months.

Another visualization of co-word analysis is shown in Figure 6, where we can see how the *Maker* co-words show the variety of 'making' as in 3D-printing as well as in 'making music'. Other co-words indicate links to the Internet of Things (IoT) and Adafruit Industries [33], an open-source hardware company developing and selling do-it-yourself electronics kits. *Hacker* tweets, however, were clearly dominated by security breaches and diverse spying affairs, traces of 'hacking' related to the Maker Movement were marginal and not under the top ten co-words.

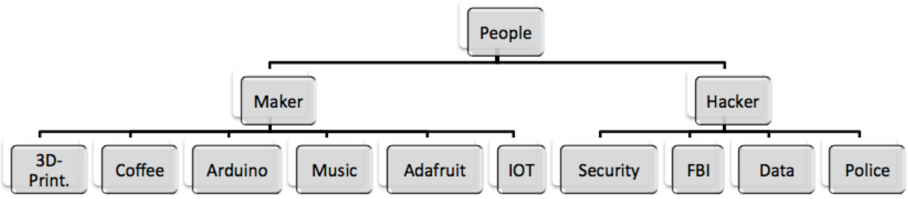

Fig. 6. Co-words for #maker and #hacker

A better understanding of how today's Internet community conceptualizes given phenomena such as 'maker space' or '3D-printing' can also be gained through an analysis of related Google searches also offered through the Google Trend service. For example, people who searched 3D-printing between January 2015 and February 2016, also searched related software or the possibility of 3D-printing metal (8th place in Figure 6).

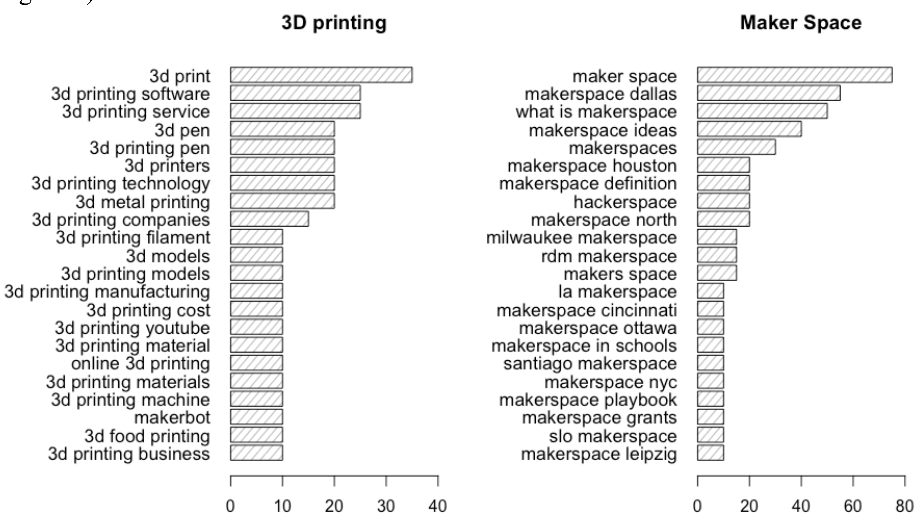

Fig. 7. Top related searches for '3D printing' and 'Makerspace' in percentages

Interestingly, printing metal also appeared on 5th place within our co-word analysis in Figure 5, indicating makers' interest in extending 3D-printing towards more durable materials. Another possible reason for 3D printing's increasing popularity could be higher awareness of novel application areas such as printing food and an increasing commercialization of 3D printing, indicated by search terms such as 'services', 'companies', 'costs' and 'businesses'. It's also informative to look back, as for example in 2013, one of the most popular related searches was '3d printing stocks', indicating people's interest in 3D printing as an investment option.

4.2 Concepts over time: Trends in Google search and Wikipedia

Another possibility to extract the taxonomic structure of the Maker Movement is to look into data provided by Google Trends, namely popularity of Google searches as well as most frequent co-occurring queries per search session [34]. Data are available since 2004 and were collected using the R package gtrendsR [35]. The data obtained from Google Trends represent total searches for a term relative to the total number of searches done on Google over time, mapping the development of a search term's relative popularity (no absolute search volumes are shown).

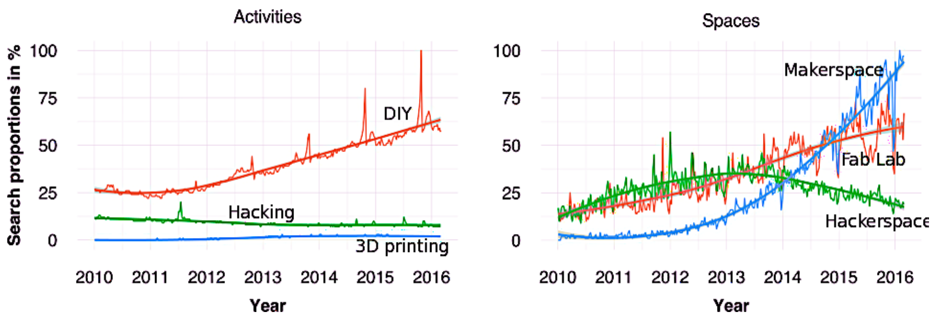

Fig. 8. Google Trends Data about 'maker activities' (left) and 'maker spaces' (right)

Figure 7 (left side) shows prototypical activities such as DIY, Hacking and 3D-printing. At this point we would argue that the diagram indicates primarily semantic differences, with DIY used for the most diverse purposes - 'making' being only one among many - and the terms 'hacking' and '3D-printing' becoming increasingly more specific and consequently referring to smaller target groups. The graphs on the right side, however, offer a clearer picture for comparison, as Makerspaces and FabLabs are on the rise and hackerspaces are declining in search popularity. With Wikipedia being one of the 'go to' sources for people who seek a first idea what a concept means, we had another proxy for general interest levels related to the 'Maker Movement'. Data have been collected through the R package 'WikipediaTrend' [36] and visualized in Figure 9. Similar to Google Trends, consultations of the 'hackerspace' page are declining after 2013 and visits to 'maker_culture' page are increasing. Overlapping with the raise of 'maker_culture' page visits is the publication of Chris Anderson's [14] *Makers: The New Industrial Revolution.* Whereas the substantial rise of 3D-Printing overlaps with another key publication, when the cover story from the Economist in February, 2011 said "Print me a Stradivarius" [37]. Other tendencies such as the decline of 'hackerspaces' (Figure 7) or the decline in access statistics of the 'DIY'

Wikipedia page (Figure 9) cannot yet be explained and need further exploration, cross-referencing data from other sources (e.g. looking into relevant social media in and around the year 2013).

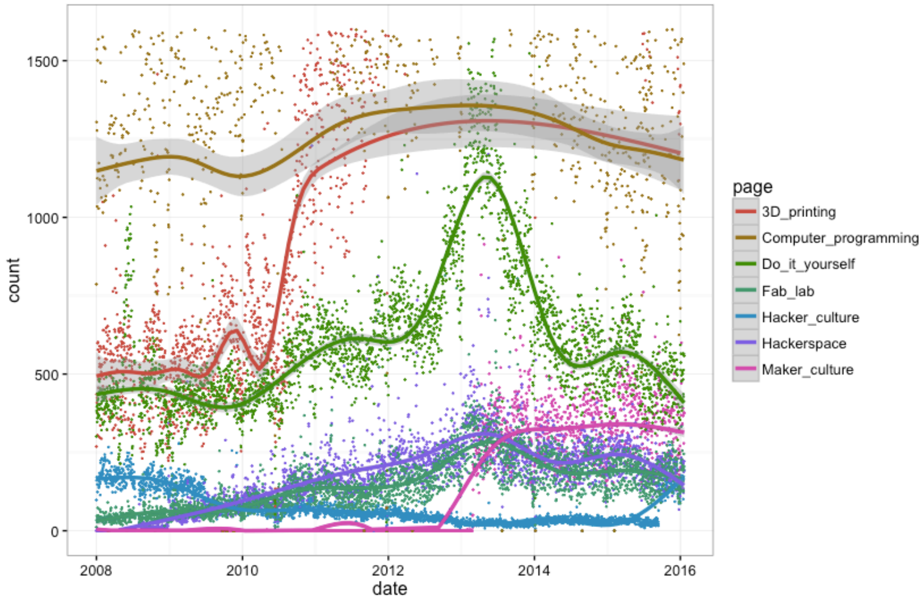

Fig. 9. Access rates to selected Wikipedia pages between 2008 and Feb 2016

4.3 Concepts and their affective implications: Emotional profiling of tweets

Beside identifying networks of related terms and trending terms, we were also interested in exploring the emotional dimensions of the tweets we had already analyzed in 4.1. Emotion analysis is already widely used in areas such as customer satisfaction [38] or the popularity of political parties. In general, the aim of characterizing the feelings present in a text can be achieved either through word-list associations (affective dictionaries and databases of common-sense knowledge) or machine learning [39]. For our purposes we used the SentiProfiler, an emotional analysis system described in [40, 41]. The SentiProfiler uses an ontology, i.e. a hierarchy of emotions derived from WordNet-Affect as the main source of emotional knowledge [42]. The WordNet-Affect ontology contains four main categories of emotions: negative, positive, ambiguous and neutral. Under each category exist several classes containing a list of emotion words. The WordNet-Affect, combines 1,316 words in 250 classes. For example, a positive feeling could fall into the class of 'liking', identified through words such as 'approval', 'sympathy' or 'friendliness' [41]. Additionally, text classification is supported by a number of disambiguation rules to exclude instances where words implying positive feelings are negated or an emotion bearing word fulfills a different role, such as the use of 'like' as a preposition, meaning 'similar to'. Analyzing the sets of tweets, we found between 0.77 and 3.3 percent of all words were emotion-bearing words (see Table 1).

Table 1. Emotion bearing words per Twitter data set

twitter data	number of words	emotion words	emotion words in percent	positive to negative ratio
3d-printing.txt	113.481	2.275	2,00%	0,87
makerspace.txt	152.330	4.134	2,71%	0,94
fablab.txt	20.193	156	0,77%	0,72
hacker.txt	149.544	4.178	2,79%	0,87
maker.txt	57.400	1.894	3,30%	0,87

From the table we notice that in general the tweets have been very positive, with a positive to negative emotion ratio of above 0.85 (with the exception of FabLab tweets). Following a more detailed comparison of #makerspace and #fablab tweets. Figure 10 shows a section of emotional expressions contained in 'makerspace' tweets compared to 'fablab' tweets, positive emotions are under 'joy' (left side) and negative emotions are under 'despair' (right side). Red nodes indicate emotions that are less than the comparative profile, green nodes indicate the emotions are more than the comparative profile and blue nodes indicate emotions only found in the 'makerspace' profile.

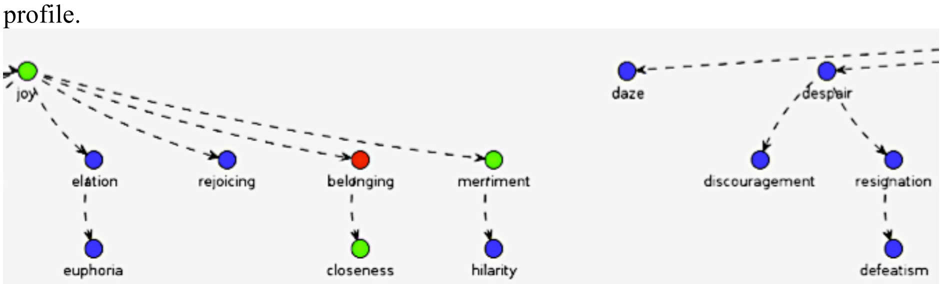

Fig. 10. Emotions in 'makerspace' tweets compared to 'fablab' tweets

To provided a more concrete picture of the analysis, we selected three tweets for positive and negative emotions, indicating a clear, an ambiguous and a false classification. Words in brackets indicate the class of emotions.

Positive emotions.

- Clear: 'Lots of *great* practical tips for creating a library makerspace' (Eagerness)
- Ambiguous: 'Huge thanks to Cargill Salt for *approving* our grant for our Makerspace. You're helping to foster creativity and innovation!' (Liking)

- False: 'Aleph objects opens new *fulfilment* center in Australia, offers free shipping - 3dprint.com ' (Fulfillment)

The ambiguous classification is not outright false, but the emotion word 'approving' refers to funding granted, rather than an approved design or a maker activity. The false classification is due to the multiple meanings of 'fulfillment' indicating either a feeling of satisfaction or the execution of a shipping order.

Negative emotions.

- Clear: 'thanks! I want to try... *afraid* I'll do most of the work in the minimal makerspace time we have!' (Distress)
- Ambiguous: *'Worried* about #makerspace logistics? #fallcue is here to help! It's not just for tech! ' (Distress)
- False: 'If kids can imagine it, they can build it! Perfect for blasting away *boredom* #makerspace' (Weariness)

In the above case, the classification is ambiguous because the distress is anticipated, not actual. Still, one could argue that makerspace logistics is characterized as a worrisome issue. Assigning the emotional class of 'weariness' to 'blasting away kids boredom' is a false classification as it is missing the negation of boredom.

Based on this first experience with analyzing the emotional value of tweets, we see a promising application area in filtering tweets and other social media expression about specific equipment, make spaces or events in order to get an impression of what might cause frustration or joy. Specific messages around logistics in maker spaces could then lead to a more targeted analysis, possibly including a wider range of social media beyond twitter, eventually leading to improved conditions for Makers.

4.4 Concept aggregation: Towards a first taxonomic structure

As indicated earlier, our intention is to combine data driven analysis with conceptualizations based on a deep understanding of the domain where the taxonomy is to be used. So far we focused on the quantitative analysis of social media and search data, yet, designing the final taxonomy will involve positivist as well as hermeneutic elements. The hermeneutic process will allow identifying ever more relevant variables and discarding less relevant variables to describe a category, thereby continuously improving categories as well as the resulting taxonomy. Identifying suitable variables that can help to structure a domain more effectively is far from trivial and categorization becomes more complex if a concept is characterized by a high number of dimensions (e.g. variables describing different types of makers) [7]. One could imagine an iterative design process, where more and more categories are empirically scrutinized.

Five types of analyses have been presented in this paper: (a) Twitter co-word analysis, (b) Google co-search analysis, (c) Wikipedia access, (d) Google search terms and (e) emotional profiling. The first two (a and b) support the identification of related concepts - the basic building blocks of the future taxonomy -, analyses (c) to (e) are more suitable to support the narratives around the identified concepts (e.g. how their popularity changed over time or whether they occur in a primarily positive or negative context). What is still missing is a technique that can aggregate single concepts into bottom-up categories.

For this, hierarchical or k-means clustering techniques can be used. Clustering algorithms group concepts in accordance to their distance to each other, i.e. "given a representation of n objects, find K groups based on a measure of similarity such that the similarities between objects in the same group are high while the similarities between objects in different groups are low." [43]. However, given the limited size of the dataset, the following cluster can only illustrate the value of clustering as an aggregation mechanism. Eventually, clusters based on a a larger dataset are likely to look differently. Fig. 11 takes 12 co-occurring keywords in tweets including '#makerspace' (cf. Fig.2) - omitting less domain specific words such as 'new', 'great' or 'today' - and clustered those keywords according to their retweeting and favoriting values. The underlying rationale for analyzing not only the frequency of co-occurring keywords but also the amount of re-tweets, for example, is the idea that retweeting is a form of joining a public discourse, publicly agreeing with someone or simply disseminating the message to new audiences [44], which are activities particularly relevant to promote the discourse needed for a more widely accepted set of categories.

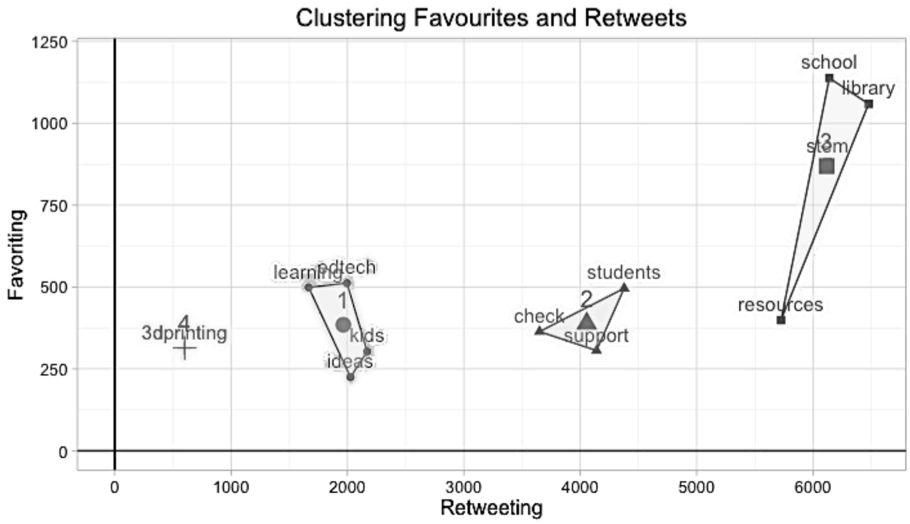

Fig. 11. Clusters in '#makerspace' tweets

A first, though loose, interpretation of Fig.11 suggests three clusters: (1) kids learning in maker spaces, (2) supporting students in maker spaces, (3) schools and libraries as maker spaces and (4) 3D-printing as a single item cluster. Hence, starting from words most frequently co-occurring with the concept of '#makerspace', we identified a shared understanding of maker spaces as places where young people learn. '3D-printing' as one of the characterizing activities in maker spaces is still present but appears to be less instrumental if judged by the number of times 3D-printing related tweets had been retweeted or favorited. Future research foci are primarily expected at the junction of specific activities and spaces, such as 'libraries as maker spaces of the future' or 'integrating a maker culture with education'. In this sense, we will aim for taxonomies which are initially limited in scope but effective in terms of their applicability as they can be created with particular spaces and activities already in mind.

5 Discussion of findings and future research

With the growth of the Social Web and participation platforms such as Wikipedia.com (creating knowledge collectively), Thingiverse.com (sharing digital designs) or Twitter (sharing generic messages), a world defined by the few is transformed into a world where almost everyone can participate [45]. Accompanying these platforms are emerging cultures of participation that offer powerful mechanisms to raise awareness of some of today's most pressing societal problems. Working towards a closer connection between empirical evidence of what potential makers are interested in and what determines current research agendas has been the broader context of this paper.

A first step towards such a nexus has been the evaluation of different data sources (Twitter, Wikipedia and Google Trends) in combination with descriptive statistics and corresponding visualizations. Based on the work presented, we suggest that a taxonomy informed by the empirical evidence of the Social Web is a more fruitful foundation for future research than a taxonomy based on concepts derived from existing literature alone. All data analyses (co-word analyses, trends, access statistics, co-search terms and emotional classifications) yielded first working hypotheses, e.g. concerning structural relationships and temporal developments within the Maker Movement.

The primary purpose of this paper was a conceptual proof of the extent to which quantitative analyses can inform taxonomic developments. It has become clear that analyzing social media depends crucially on good research design including the selection of keywords as filters, types of data requested, period of data coverage, etc. - data sets which are too small or covering a too short time span are likely to be unduly influenced by single events or opinions. This paper presented a process, some quantitative methods as well as some first experiences with a datasets describing

A full taxonomy for the maker movement would also require a stronger qualitative analysis for the hermeneutic interpretation of the identified concepts. Future work will therefore include larger datasets, a hermeneutic process and a more systematic design of iterations, gradually refining taxonomic structures.

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