A new method for visualizing the relatedness of scientific areas is developed that is based on measuring the overlap of researchers between areas. It is found that closely related areas have a high propensity to share a larger number of common authors. A methodology for comparing areas of vastly different sizes and to handle name homonymy is constructed, allowing for the robust deployment of this method on real data sets. A statistical analysis of the probability distributions of the common author overlap that accounts for noise is carried out along with the production of network maps with weighted links proportional to the overlap strength. This is demonstrated on two case studies, complexity science and neutrino physics, where the level of relatedness of areas within each area is expected to vary greatly. It is found that the results returned by this method closely match the intuitive expectation that the broad, multidisciplinary area of complexity science possesses areas that are weakly related to each other while the much narrower area of neutrino physics shows very strongly related areas.

I. INTRODUCTION

Understanding the growth and evolution of academic research areas is important to assessing the health and influence of scientific areas and can provide potentially important predictive capability in assessing technologies that may emerge from fundamental and applied research. A consequence of the large and growing number of highly specialized research areas is that identifying the productive intersection of these can no longer be done manually. However, the ready availability of computing power, the large frequency of published work and the relatively high data integrity of bibliographic databases provides the elements necessary for automated screening and visualization of these interdisciplinary areas.

The visualization of research areas is an active area in bibliometric studies, largely using clustering of individual units to describe the relatedness of research areas. The primary metric conferring this relatedness has historically been the citation frequency, with the individual unit of measure being an instance of one publication citing another. Using publications as nodes, a very complicated unweighted directed network could be formed relating publications together. Since this is visually confusing, the practice of re-assigning these nodes as either authors or journals is preferable, resulting in a weighted network map where the clustering observed in these networks broadly reflects the topical areas of study, creating a variation of what is traditionally referred to as a knowledge map. Intuitively, these methods work well at understanding the relatedness of topical areas because authors tend to cite research in the area of their study more frequently and journals tend to publish work that caters to a specific, topical focused scientific community. Of value in these visualizations are the areas of study that lie between topical clusters that represent interdisciplinary research, which can often give rise to emerging scientific areas.

While the methods described above use citation as the fundamental unit of measure, we offer an alternative approach by showing how counting the occurrences of the same author working in multiple areas can provide the necessary linking to relate these multiple areas to each other. Intuitively, this approach is motivated by the observation that scientists working in one area of study will work in related areas of study more frequently than in unrelated areas, and so we expect a stronger connection between closely related areas. The approach we carried out produces an undirected, weighted network map that differs from the practice described above in the following ways: (1) the nodes themselves are the topical areas of study, (2) the weight of the link connecting one node to the next is proportional to the number of authors shared between those topical areas (adjusted for area size), and (3) the clustering observed will define a major topical area composed of closely related topics. In general, the network constructed in this way can be thought of as a bipartite graph where one set of nodes corresponds to authors and the other set to the areas that the authors participate in. In principle, the structure of this network is amenable to analysis with many clustering or community detection algorithms. One of the values of using common authors over citations is that the links observed are much stronger since they require authors to develop deep expertise in these areas in order to publish successfully in them, as opposed to a simple understanding of the work executed, which is the minimum requirement to cite another’s work in the case of citation patterns. In this paper, we develop the procedures for establishing this link, in particular correcting for name homonymy in a statistical way.

This approach is also useful for examining interdisciplinarity, which we define here to be a feature arising from the participation of two or more vastly different areas of study in terms of expertise, knowledge or training. Our concept of relatedness is measured by the overlap in participation of researchers in two different areas. Large overlaps in participation between two or more areas indicates strong relatedness. Low overlaps in participation between two or more areas indicates poor relatedness. In a very simple example, if two areas belong to separate clusters with little or no relatedness to each other, but both areas have strong relatedness with a third area, that is indicative that the third area is interdisciplinary since it draws on the participation of two, unrelated areas.

For our case studies to demonstrate this methodology we
intentionally selected two different fields: the *complexity sciences* and *neutrino physics*. While the latter is a traditional, narrow field of study that is deeply rooted in physics, the former is a multidisciplinary field that intersects with many other scientific areas, drawing upon the talents of many different types of scientists. For this reason we intuitively anticipate a stronger degree of relatedness in *neutrino physics* than *complexity science*, and show that the method we developed confirms that intuition. Last, we point out that while a significant number of methods in bibliometrics focus on relationships between authors and papers (i.e. co-authorship or citation patterns) that elucidate the structure and pattern within these areas, this approach focuses on the relationships between these areas.

II. METHODOLOGY

The publications used to generate the common author graphs were drawn from the Institute for Engineering and Technology’s Inspec publication database as accessed through the Thompson Reuter’s ISI Web of Knowledge v5.5 index. Once the Inspec database was selected through the Web of Knowledge search interface the Boolean keyword or series of keywords best representing the field under investigation were entered into the Inspec search field. For clarity, the term sub-field will be used for these specific searches, where it is understood that the keyword search was structured in such a way as to extract a scientific community that is engaged in studying a field will be used for these specific searches, where it is under-entered into the Inspec search field. For clarity, the term sub-field will be used for these specific searches, where it is understood that the keyword search was structured in such a way as to extract a scientific community that is engaged in studying a sub-field (i.e. social cybernetics) that happens to also be part of a larger field of study (i.e. complexity science). The generic term “area” will be used when the context could conceivably pertain to both field and sub-field. This is a subject matter expert managed process. In general, keywords that are most closely associated with a field of study were selected such that it would conservatively capture papers within the field of interest. There is some variance between keywords and spot-checking the articles by a subject matter expert within the area was used to validate that each keyword pull consisted of only relevant articles. However, the method described here is not limited to keyword searches and can be applied to classification indices, journals, university research output, or any arbitrarily chosen group of articles.

The search was performed over the years 1969-2012, the longest time span available in the database, however the vast majority of searches returned results with shorter durations. Each keyword search typically returned 10^8 to 10^9 publications. A custom Python script was written and used to preprocess the database by sub-fields to extract a list of authors, where the last name and initials were stored, and repetitions were removed. This produced a list of unique authors for every keyword search. These lists were then compared with each other to determine the number of authors the lists had in common. A symmetric matrix of pairwise comparisons was generated in this way using fast search algorithms in Python. Typical computing times were on the order of a few minutes for the generation of individual topics lists, while the overlap between topics required on the order of several hundred searches over the sub-fields and took approximately half an hour, using server-class hardware.

III. DISCUSSION

As a first approximation to quantifying the link between any two fields of study one can postulate the number of authors common to both fields. Unfortunately this naive approach suffers from two deficiencies that precludes its use as a measure of overlap: area size dependence and noise. Intuitively, it can be reasoned that the number of common authors depends in some way on (1) the number of authors in each topic, which varies by several orders of magnitude based on area size, and (2) the probability of false positives that arise from matching two authors that are different people with the same last name and initials. These occurrences, though rare, cannot be eliminated easily and are globally present and mostly uniform. For these reasons they will be referred to as noise arising from name homonymy, which is a persistent problem in bibliometrics. Below, we develop a treatment for both of these effects.

A. An Equation to Handle Multiple Fields of Different Sizes

First, we develop a treatment to deal with the large variation of area sizes that will affect the number of common authors in the pairwise matching. In what follows we try to derive an expression for the number of matches as a function of list sizes and how they relate to the probability of finding name matches. We have not found a simple exact derivation of a formula relating these quantities but procedurally we offer a formula and motivate it using some simplifying assumptions and show how the said formula is justified for our purposes by comparing its results to a Monte Carlo simulation.

Let us consider a pool of names and from it extract two lists of names, \( N \) and \( M \), containing \( n \) and \( m \) elements respectively and with no loss of generality assume that \( n \leq m \), and that the names be unique within the lists, but not necessarily between each other. Let us start by comparing one element of \( N \) to one of the elements in the list of \( M \) and further assume that there exists a probability \( p \) for an element of \( N \) to be matched to an element of \( M \). There are two outcomes: the element either matches that entry in the list with probability \( p \), or it does not (with probability \( 1 - p \)). Since there are \( m \) elements in \( M \), the probability of finding no matches between the first element in \( N \) to the entire list of \( M \) will be \( (1 - p)^m \). However, we are not interested in the case of no matches, but in the case of matches, that can now be approximated by: \( 1 - (1 - p)^m \), as the probability that a single element in \( N \) will match an element in list \( M \) (strictly speaking the last expression represents also the case of multiple matches but we assume the chance to be small and actually precluded by the assumption that each list has no internal matches). Now we proceed to develop an expression for comparing the entirety of both lists to each other. As a first approximation we can multiply the probability of the single element matching case by the num-
ber of elements, \( n \), to produce the expression in Equation 1, where \( E(k) \) is the expected number of matches between the lists of size \( n \) and \( m \) (this value \( \bar{k} \) will be later approximated by the number of matches obtained from real data)

\[
E(k) = n(1 - (1 - p)^m)
\]

(III.1)

For our purposes, the unknown variable is \( p \). In order to make use of Equation [III.1], we rewrite the variables from their expected values to their measured values. Thus, \( \bar{k} \) will be an estimate of \( E(k) \), and \( \bar{p} \) will be an estimate of \( p \). Solving for \( \bar{p} \) produces the functional form of the equation we will use.

\[
\bar{p} = 1 - \left(1 - \frac{\bar{k}}{n}\right)\frac{1}{m}
\]

(III.2)

Equation [III.1] is just an approximation and worth noting how it may fail and in what regime. First as we compare lists every time there is a match the second list should be reduced by 1 and the probabilities should be adjusted accordingly. This could be accounted for by trying to perform an exact calculation or perhaps by intuitively postulating an effective \( m^* \) that is somehow smaller than \( m \). In practice, we expect that since \( p \) and the numbers of matches are small, the formula will still be a valid approximation. Notice also that we do not expect the formula to be symmetric with respect to \( n \) and \( m \) since we have assumed that \( n \leq m \).

In order to validate our use of these approximations, we carried out a Monte Carlo (MC) simulation of the exact solution over the range of \( n \) and \( m \) within the lists used in this study by generating matches between list for different values of \( p \), computing an expected number of matches \( \bar{k} \), and trying to recover the initial value of \( p \) by using Equation [III.2]. The MC simulation takes two integers \( n \) and \( m \) and with probability \( p \) generates matches. This procedure introduces the nuances we do not treat in our derivation, like the fact that once a match is found then the largest list is reduced. The MC simulation also calculates only single matches as opposed to accounting for multiple matches as in the assumptions above. The result is that for sizes within the ranges used, there was less than 5% error between the Monte Carlo result and the analytical expression on Equation [III.2] supporting our use of the latter as a valid approximation. Briefly, an example calculation looking at two fields consisting of 1000 authors (\( n \)) and 10,000 authors (\( m \)) that happens to have 100 matches \( \bar{k} \) between them allows us to use Equation [III.2] to calculate the probability (\( p \)) to be

\[
1 - \left(1 - \frac{100}{10000}\right) = 0.105 \times 10^{-5}
\]

As a check, we compare this to what the MC simulation would predict as the number of matches given the same \( N \), \( M \), \( p \) and obtain 98.8 matches while Equation [III.2] would predict 99.6 matches, representing an error of less than 1%.

B. An Approximation to Noise Arising from Name Homonymy

Now that an expression for the matching probability has been developed, it can be used as a measure of the strength of the link between various areas of study, which describes the overall probability that authors in one area will also publish in the paired area. While that is the focus of this study, it is first important to characterize the amount of noise arising from name homonymy. The statistics arising from the matching probabilities as calculated from the number of matched authors (the pairwise comparison matrix described in the methodology) can be used to determine this noise factor. To do this, we choose pairs of fields in which we intuitively expect to find no true overlap of common authors, implying that the overlap found is due solely to name homonymy. Specifically, we apply Equation 2 to the pairwise comparison of 25 fields within *neutrino physics* to 25 fields within *complexity science*. This produces a matrix of values of matching probability that describe the occurrence of name homonymy. We plot the histogram of these values in Figure 1, Top. The histogram shows a very broad, skewed distribution of probabilities with a second delta-like distribution centered at zero. The median value of this distribution is \( p = 1.62 \times 10^{-6} \), which is representatative of name homonymy since the fields compared in this way have very little relationship to each other. The broader distribution is related to the name homonymy error, whereas the delta-like peak at zero is a result of matches from lists with very small numbers of authors where zero is a very likely outcome. In order to validate this against ground truth, the list of authors identified in this way was randomly spot-checked by selecting 20 authors at random and using the open source search engine Google along with the affiliations listed in their papers to find the specific individuals. It was verified that all of the common authors found in this way corresponded to two or more distinct individuals, thus lending support to our assertion that this is a reasonable method to estimate the level of name homonymy. A larger and broader sampling will help establish the estimated error, but based on the result that the 20 selected had no homonymy errors, it is expected errors generated in this way range from 0-9% within a 95% confidence interval.

C. Case Study: Neutrino Physics vs. Complexity Science

Similar statistical analyses were then carried out on the areas of *neutrino physics* and *complexity science*, comparing fields within each area inclusively. In Figure 1 Middle, a histogram plotting the matching probability values of the pairwise comparison matrix of *complexity science* is shown. It can be seen that while there is a large number of matching probability values that correspond to the peak of the name homonymy noise, there are a significant number of matches that far exceed these values. The median value of this distribution is \( p = 4.13 \times 10^{-6} \) and is representative of the amount of name homonymy plus participation of complexity authors in multiple sub-fields. Still, its similarity in the peak of the distribution to noise suggests that this is a very weakly related area of study where there are very few common areas between fields. For example, if we divide the medians in this way to simulate a signal-to-noise ratio (S/N), we obtain

\[
4.13 \times 10^{-6}/1.62 \times 10^{-6} = 2.55
\]

which is generally consid-
of this distribution is $p = 5.38 \times 10^{-6}$ and is representative of the amount of name homonymy plus participation of neutrino authors in multiple sub-fields. This is more than an order of magnitude larger than the complexity science median. This indicates that the field of neutrino physics is very strongly related, with a large number of scientists in one sub-field publishing in many others. Using a similar signal-to-noise argument as complexity science, it is found to be $S/N=33$, which is generally considered to be a relatively strong signal. This also matches our intuition since we know that this area of study is very deeply rooted in physics, requiring very expensive specialized instruments and a much smaller, less diverse physics-oriented community. Physicists studying neutrinos have a very similar skillset and training and in fact not only use similar but sometimes the same equipment.

Using the medians of the distributions as a measure of the differences in relatedness of the two sub-fields, we calculated the ratio (subtractively corrected for name homonymy noise) to be 22.4 times more likely for an author to publish in multiple sub-fields if they are in neutrino science than in complexity science. A complete summary of these statistical calculations appears in Table II.

Now we use the statistics gathered to define the link strength ($l$) to be the matching probability ($p$) between fields within complexity science and neutrino physics minus the mean of the matching probability ($p_0$) of the name homonymy between complexity science and neutrino physics,

$$l = p - p_0 \quad \text{(III.3)}$$

A plot of the fields of complexity science and neutrino physics are shown in Figure 2, where a higher link strength is represented by the thicker line weights for the lines connecting each node.

We observe additional intuitive verification when looking at the relative link weighting. For example in complexity science, very thick weighted lines connect the social related areas: social network, social simulation, social systems, social cybernetics. Additionally, areas where there is little connection also bears out our expectations. For example, the only sub-field connected to particle swarm is swarming behavior, as expected. Sub-fields which are subsets of each other also possess strongly weighted links as expected. For example in neutrino physics, there is a very strong link between beta decay and neutrinoless double beta decay, as papers (and therefore authors) of the former sub-field also contain papers from the latter since the keyword of the former is included in the latter.

D. Other applications of SCAN

For this case study, we have shown that this method produces results that we intuitively expect, in order to validate the underlying assumptions concerning the area participation of authors. In general, however, this method can be applied to any arbitrary grouping scheme. As this method uses the overlap of authors within groupings, it allows the user to test...
Table I: Statistics of the distribution of matching probabilities ($p$) for complexity science, neutrino physics and the name homonymy are shown comparatively. Signal-to-noise ratios ($S/N$) are given for each field (CS or NP) with respect to using name homonymy as the noise, $N$. Additionally, treating the noise as a background, the actual signal can also be obtained subtractively ($S - N$). It is also useful to compare how much of a difference a highly related field is to a low relatedness field by looking at the ratio.

| Name Homonymy (N) | Median ($\times 10^{-6}$) | Mean ($\times 10^{-6}$) | $\text{Median}(S/N)$ | $\text{Median}(S - N)$ |
|-------------------|--------------------------|-------------------------|----------------------|------------------------|
| Complexity Science (CS) | 1.62                     | 1.80                    | 2.55                 | 2.33                   |
| Neutrino Physics (NP)   | 53.8                     | 69.4                    | 33.2                 | 52.18                  |
| Ratio (NP/CS)           | -                        | -                       | -                    | 22.39                  |

Figure III.2: Network structure of the fields of *complexity science* (top) and *neutrino physics* (bottom) showing the relatedness of sub-fields of study (nodes) as determined from the number of authors that are common to each sub-field of study (adjusted for sub-field size and corrected for name homonymy noise). The thickness of the lines represents the link weight and is proportional to the matching probability between sub-fields. Note that for clarity, the link weights are consistent within the top and bottom figures but not relative to each other; if done this way, then the lines in the top graph will be too faint to see.
ture work is planned to explore this more accurately. It is possible to use the same level of name homonymy as calculated in this study as a correction factor for other studies since it should be measuring a global phenomenon, but the method outlined here provides way forward to estimate this more accurately by including more disparate areas if that is desired.

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