Theory Identity: A Machine-Learning Approach

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Abstract

Theory identity is a fundamental problem for researchers seeking to determine theory quality, create theory ontologies and taxonomies, or perform focused theory-specific reviews and meta-analyses. We demonstrate a novel machine-learning approach to theory identification based on citation data and article features. The multi-disciplinary ecosystem of articles which cite a theory's originating paper is created and refined into the network of papers predicted to contribute to, and thus identify, a specific theory. We provide a 'proof-of-concept' for a highly-cited theory. Implications for cross-disciplinary theory integration and the identification of theories for a rapidly expanding scientific literature are discussed.

1. Introduction

To better identify, understand, and utilize the dozens of related and overlapping behavioral theories across disciplines, ongoing research seeks to create formal-theory ontologies and related taxonomies [8]. The continuous identification of quantitatively-based theoretical instances, which *subscribe* to a specific theory, is critical to ontology creation and to theory evaluation [1]. But the exponential growth of the body of scientific literature has made it increasingly difficult if not impossible for researchers to comprehend the volume of research in their disciplines and even in their own areas of specialization [2]. A critical aspect in this comprehension is the ability to *identify* specific theories which "account for some subset of phenomena in the real world' [1, p. 4] and be able to differentiate said theory from similar but distinct theories. Once theories are identified meta-analysis, comparative evaluation, integration, ontology creation, or falsification can occur.

We argue that a theory's identity is not simply specified by the original publication proposing a given theory, nor by the most recent or most cited version, but rather consists of the set of publications including the originating publication, the most influential extensions of the original article, and all theory-subscribing articles. Thus a theory is contained within and bounded by, the corpus of publications that subscribe to a theory. *Subscription* is determined by whether a research publication intentionally and empirically contributes to theory development or merely invokes the theory while providing contributions unrelated to the invoked theory. *Subscription* may include theory extension, testing, identification of theory boundaries, or meta-analysis within the theory domain [1, 3], and does not evaluate whether a publication actually contributed to the theory, just the *intention to contribute*. Improved techniques for identification of relevant research—and a reliable method for determining which papers actually subscribe to a theory, are necessary to successfully identify a specific theory and integrate subscribing articles into a cumulative research program or ontology.

Recent work arguing for inclusive ontologies of behavioral theories identify dozens of major theories of human behavior [4]. Some of the 83 theories included by Hobbs et al. [4] have been cited more than 10,000 times (e.g. the IS theories Technology Acceptance Model (TAM) [5, 6] and the Unified Theory of Acceptance and Use of Technology

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(UTAUT) [7], making comprehensive meta-analytic reviews challenging for a single theory and near impossible for the whole set of theories. For example, although publications may reference a specific theory, Williams et al. [8] found that less than 10% of the articles citing UTAUT [7] actually contributed to the theory and less than 4% had tested the full theory [8], which renders citations to a theory an unreliable gauge of subscription and potential contribution. Leading to a malignly complex situation, contributions to some theories potentially also contribute to similar theories, and such cases are often easier detected when the target theory is known.

The rapid expansion of behavioral research in psychology, sociology, behavioral medicine, information systems, management, marketing, nursing, economics, and communication leads to construct proliferation [9, 10] and hampers efforts to perform meta-analysis [11, 12]. Despite decades of work dedicated to developing and testing behavioral theories in these disciplines, cumulative knowledge, innovation, and disciplinary consensus have been quite modest [10]. Rather than refining and strengthening the explanatory capacity of theories and thereby enabling interventions and innovation, many researchers tend to follow ephemeral phenomena and disciplinary fashion waves [13], all while scholarly reward systems encourage reinvention and renaming [9].

Meta-analysis and structured reviews are instrumental in increasing the verisimilitude or 'truthiness' of theory [14]. The creation of theory ontologies formalizes and conceptualizes individual theories and enables the transfer of findings across theories, a simple example being that findings from TAM's relationships between *ease of use* and *usefulness* should directly transfer to UTAUT's *effort expectancy* and *performance expectancy*. But the *sine qua non* of theory ontology is discrete, clearly identifiable *theory identity*. Prior research on theory construction [15], evaluation of theory quality [1], and categorization of theory [16] illuminates the need to isolate a theory amid a large number of papers that provide variants to the original exposition. Meta-theoretical analysis can identify theory domains [3] by depicting the empirico-nomological network of constructs and associations reported in the literature but cannot discern distinct theory variants nor identify which publications contribute to extension or refinement of a specific theory. Building on Weber [1], each article extending or testing a given theory represents an instance of that theory. The incremental knowledge created about a specific theory through the constant testing of different variations has no meaning unless these findings are aggregated and integrated. We here argue for theory identity as the combination of all relevant theory-subscribing articles for any given theory.

The issue of theory identity is significant for popular theories when all contributions to the theory must be evaluated. For example, according to Google Scholar, the theory-initiating articles for TAM [5, 6] had received 16,300 and 9,050 citations respectively by June 10th, 2013. Of these, 2,320 and 1,270 citations were received in 2012 alone, suggesting that integration and evaluation of all new research ideas that are intended as contributions to TAM currently borders on the impossible. That TAM, like many other theories, has multiple theory-initiating articles complicates the search and integration process. Having every research contributor to a theory (such as TAM) evaluate thousands of papers is unwieldy and unrealistic; for this reason, an open portal that detects papers which subscribe to a given theory, stores the findings, and makes those findings available to researchers is called for [17]. In medicine, where systematic reviews are considered absolutely crucial for treatment decisions, use of machine learning has recently been proposed as a way to improve retrieval of studies [18] and integrated into open portals [17]. We argue that such approaches must be developed for behavioral theories, and methods are needed that will apply to theory networks and can be implemented along with open portals.

This research focuses on the problem of theory identification through a novel, machine-learning approach. Application of machine-learning methods of article citation analysis demonstrates the efficacy of our approach in isolating research articles that subscribe to—and thereby identify—a specific theory [19, 20]. In turn, this allows researchers to examine that corpus to identify the constructs and associations that comprise the structure of a given theory. In addition, this technique crosses disciplinary boundaries allowing analysis of the degree to which non-IS disciplines contribute to specific theories. This study applies machine-learning analysis of text and citation-based information to one specific theory, the Technology Acceptance Model [5, 6] in the process of developing and testing the *Automated Detection of Implicit Theory* (ADIT) system.

2. Theory-Citation Networks and Theory Identity

Locating a *theory* in a citation network is problematic given that it is not clear what it means to *contribute* to a theory. In other words, what role do individual articles play in a theory? Following Weber [1], we see theory as an amalgam of all the instances of articles that subscribe to that theory. This is evidenced by the claim that support for a theory "grows when its powers of prediction and/or explanation remain robust across different tests of the theory" [1 p 16] indicating that a given theory can be identified by the set of papers which are considered to subscribe to the theory. For the purposes of this article, the composition of the amalgam is not important, just discovering which articles are admitted into the class of articles that subscribe (intended to contribute) to a focal theory. Consequently, a theory can be identified by the set of articles that subscribe to that theory. Criteria for membership in the subscribing set must be determined.

We use authors' intention to determine whether an article subscribes to the focal theory. The authors' intention to contribute must be explicated through the article, and may be evaluated based on: whether they cite the focal theory; retain construct names from the originating theory (e.g., do not rename existing constructs); include at least one construct from the originating theory; discusses findings in the context of the originating theory; and retain the theory name. Further, for our purposes the article must be empirical in nature (though not necessarily quantitative. By focusing on intention, we set aside the expanded definitions where construct synonymy indicates contribution. Per our earlier example, it is easily argued that any article that is grounded in UTAUT and that examines the key UTAUT relationship between *performance expectancy* and *effort expectancy,* contributes to knowledge about TAM's relationship between *usefulness* and *ease of use* due to their near identical operationalization [7]. However, given the stated intention of Venkatesh et al. (2003) to create a new theory, the provision of a new theory name, and the renaming of existing constructs, UTAUT is in this scheme treated as distinct from TAM. Once contributions to UTAUT and contributions to TAM have been separately enumerated, creation of an ontology will be easier in that the synonymous constructs in these two theories may be linked and findings transferred.

To identify contributions to a focal theory, we go beyond Weber's terminology [1]. For Weber, the *domain* of the theory is the phenomenon for which a theory provides an account; specifying further, the *focal phenomenon* is the class of things for which the theory accounts—the dependent variable. We here define a new concept, *theory ecosystem,* as the set of research publications influenced by a theory in addition to those publications' other influences. Extending this definition, we posit the theory ecosystem as the set of articles that have the *potential* to influence the focal theory by contributing to the operationalization, application, testing, and understanding of the theory.

The ecosystem is a multi-level concept. The first level (L_1) of the ecosystem is operationalized as the set of theory-initiating articles [e.g., 5, 6]. The second level of the ecosystem is made up of every article that cites an L_1 article. L_3 comprises every article cited in an L_2 article, except for those cited articles that have already been assigned to L_1 or L_2. Figure 1 shows the three levels, including examples in which L_2 articles cite each other and L_2 articles cite L_3 articles. Because only L_3 articles without citation records could potentially contain a non-assessed citation to L_1, L_3 articles with citations records were much less likely to be important contributors to the theory ecosystem. Therefore, L_3 citation records were not collected. Not shown in the figure, an L_1 article may cite a L_3 article but not a level-two article because by definition, L_2 articles are published after L_1 articles whereas L_3 articles may in some cases have been published before L_1 articles. In Figure 1, it is shown that A_4 receives a higher proportion of citations from other L_2 articles, and the same is true for A_7, suggesting a higher likelihood of it being a theory-contributing article.

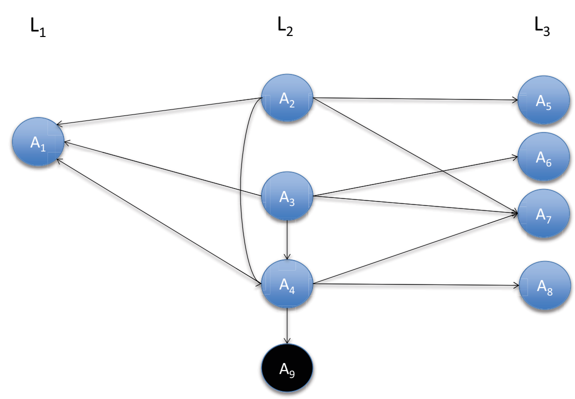

Figure 1. Theory Ecosystem Principle

A_9 represents what we'll term a "black hole" in that low data quality means that the article does not have a citation record associated with it, and can only be detected if an article with an available citation record cites the black hole.

A theory ecosystem will often refer to theories that existed before the focal theory as well as to theories that were initiated after the focal theory. Every theory will have its own ecosystem and no two ecosystems are identical (unless one article proposes two different theories). For theories in similar domains, there will likely be large overlaps between different theory ecosystems. For example, we expect the theory ecosystems of TAM and UTAUT to be highly overlapping whereas the theory ecosystems of TAM and the Affective Events Theory [21] will not significantly overlap.

Given the assumption that a paper must cite the theory-initiating article to be a contributor to that theory, the two reasons for including the third level need addressing. First, to create an accurate network between the articles in the network, indirect relationships need to be addressed. In Figure 1, A_7 is cited by A_2, A_3, and A_4. This chain of influence would be lost without level three, and algorithms would have no way of modeling the potential similarity of the three L_2. Second, in cases of low data quality, key theory-contributing articles may be discarded. For example, if a database of articles does not contain the citation record for A_3, algorithms could never evaluate it as a potential contributor to the focal theory. In fact, for Figure 1, without L_3, and with data-quality problems, the only network information available would be that A_2, A_3, and A_4 cite the L_1 article. Given this, whereas L_3 articles should always be examined to create a full network, once this network is available and has been used fully to evaluate the influence of all L_2 articles, in cases of good data quality, only L_2 articles should be evaluated as potential contributions to the focal theory.

3. The *Automated Detection of Implicit Theory* (ADIT) technique

The Automated Detection of Implicit Theory (ADIT) technique detects boundaries of behavioral theories. Rather than focusing on the theory structure or the constructs encompassed by a theory [1, 16], we identify theories through the network of papers which advance the development of a theory. This technique enables researchers to build, analyze, and visualize large-scale theory networks and has two initial goals:

1. To accurately detect which articles subscribe to a focal theory and thus identify the theory and its constituent components.
2. To provide a constantly updated account of new contributions to a large set of behavioral theories.

3.1. ADIT Network Construction

ADIT starts with the assumption that there is general agreement on which article(s) initiated a specific theory. For example, the Technology Acceptance Model, was first initiated by Davis [5] and Davis et al. [6],[1] whereas the Unified Theory of Acceptance and Use of Technology was initiated by Venkatesh et al. (2003).

ADIT was designed to use multiple available-literature databases. For this article, only Microsoft Academic Search (MAS) was used because of its Application Programming Interface (API). The first step in use of ADIT is to use MAS (http://academic.research.microsoft.com) to find the unique MAS identifiers for all theory-initiating articles. For TAM these are 1265954 [6] and 1253523 [5] for the initiating articles. Once the theory-initiating articles for a given theory are selected, the MASCrawler is initiated. The MASCrawler class is a concrete implementation of ICrawler specific to Microsoft Academic Search, which handles the retrieval of articles, keywords, authors, citations, and references. It utilizes the RateLimit class to facilitate conformance to MAS's rate limit (avoiding overtaxing of Microsoft servers).

Once the relevant crawls have been enumerated, the crawler goes through the following process: if the crawl is a new crawl, the Crawler retrieves information regarding the canonical articles, first checking if there is a current record of the canonical articles (retrieved as part of a previous theory crawl) and retrieving them from the MAS record if they do not exist; if the crawl is a scheduled crawl that was interrupted during citation enumeration, the queued citations will be removed from the queue to avoid creating duplicate citations. Each canonical article has its existing citations enumerated and compared to the latest citation data from the MAS record. If there are any additional citations, they are queued for processing.

Citations are de-queued, with the corresponding article either being retrieved from the persistence model or, if the model doesn't yet exist, the MAS record. The retrieved article is then set as citing the corresponding canonical article. The references (papers listed in the "References" section) of each article in the previous step are compared to their existing references, with any new references being queued.

References are de-queued, with the corresponding article either being retrieved from the persistence model or, if the model doesn't yet exist, the MAS record. The retrieved article is then set as referencing the corresponding first-level article. Once these articles and their references have been stored in the

[1] Arguably, TAM was initiated by Davis' 1986 dissertation, which would have added a few articles on top of Davis (1989) and Davis et al. (1989).

ADIT database, each article cited in these L_2 articles is downloaded, leading to a full set of theory ecosystem articles. At this point, all network connections are enumerated in a network, and ADIT moves on to the next step, assigning importance to all articles using a new article-level Eigenfactor algorithm.

3.2. Applying Article-level Eigenfactor

Network theory offers a powerful set of tools for identifying important papers and communities of papers in citation networks. The most popular network ranking algorithms (e.g., PageRank) work well on networks that are nearly ergodic–that is, on networks where the random walker can take long paths from one point in the network to any other part of the network. For this study, we work with article-level networks–networks that are not ergodic. Due to the temporal nature of these systems, citation trails move inexorably backwards in time. To correct for this, we modify the flow-based approach to deal with these time directed acyclic graphs. This method is called the article-level Eigenfactor score.

The modifications require shorter paths for the random walker. If the long paths are used, older papers are disproportionally weighted. The algorithm also makes adjustments to the teleportation process. Teleportation corrects for the non-ergodicity of most networks but is not something we want to encode in the dynamics. Therefore, we teleport to links and split the flow equally between out-links and in-links to determine stationary distribution, and then follow the out-links in a subsequent move from each node. Because we teleport to links, this allows us to use short paths without ignoring the network structure. We give credit for being cited but not for citing, because we use the directional information in the ranking step. As a result, the two-mode dynamics handles time bias much better for ranking. For mapping, the two-mode approach is similar to a long Markov chain, but it ignores the accumulation of teleportation and only encodes the important ranking steps.

The first version of ADIT uses 15 features of articles in the theory ecosystem to train a set of algorithms that detect theory-contributing articles.

1. Article-level Eigenfactor: Every article in the theory ecosystem is assigned an Eigenfactor score reflective of its importance in that network. This becomes the first feature into the machine-learning process. Features 2-4 are all derivations of the Eigenfactor score.
2. Theory-attribution Ratio 1 (TAR^1): This feature examines each focal article's references, sums up the Eigenfactor score for each L_2 article (those that cite the theory-initiating articles), and divides that score by the total number of citations (A_c) in the focal article. This feature works under the assumption that knowledge of the key citations to the theory-initiating articles is more likely to indicate an intention to contribute to that theory.
3. Theory-attribution Ratio 2 (TAR^2): This feature sums up the Eigenfactor score for each L_2 article that is also a positive training case for each focal article and divides by the total number of citations in the focal article.
4. Theory-attribution Ratio 3 (TAR^3): This feature mirrors TAR^2 but without a denumerator.
5. Impact Factor: This feature calculates the impact factor of an article [22].
6. Number of citations (C_n): How many citations does the article contain?
7. Year: Because theories tend to have a life-cycle, knowing the year of publication should enable the system more accurately to evaluate whether a article is intended to contribute to a theory.
8. Depth: A determination of whether the article is second- or third-level. This feature should be important only in cases of low data quality, where it is not possible to assume that only level-two articles may contribute to a theory.
9. Journal id: Some journals are more likely to publish articles related to specific theories. For TAM, *Information & Management* has been remarkably supportive.
10. Theory name in Title (T_t): Does the theory name or acronym exist in the title. In this case, *Technology Acceptance Model* or TAM.
11. Theory name in Abstract (T_a): Does the theory name or acronym exist in the title. In this case, *Technology Acceptance Model* or TAM.
12. Construct 1 in Title or Abstract (C_1): Does the key TAM construct *ease of use* exist in the title or abstract?
13. Construct 2 in Title or Abstract (C_2): Does the key TAM construct *usefulness* exist in the title or abstract?
14. Construct 3 in Title or Abstract (C_3): Does the key TAM construct *behavioral intention* exist in the title or abstract?
15. Construct 4 in Title or Abstract (C_4): Does the key TAM construct *use* exist in the title or abstract?

Features 10 through 15 are based on simple text pattern matching, changes for each theory examined, and require expert knowledge of the theory.

3.3. Machine Learning

A set of 300 random articles was drawn from L_2 of the TAM ecosystem (see Table 1), of which we were able to access 297 for examination. Nine articles were excluded because they were in foreign languages (German (4), Chinese (2), French (1), Korean (1), Indonesian (1)) and nine articles were excluded because of poor data quality in MAS (no citations to TAM in the articles upon examination). This left 277 articles for analysis, of which 186 were used for training and 91 for validation samples. These articles were examined manually both by an experienced research assistant and also by a senior faculty member and disagreements resolved. An additional evaluation set was created based on 120 articles identified as empirical TAM articles in several TAM meta-analyses and review articles along with a set of 10 randomly selected and evaluated negative examples.

Table 1. TAM Ecosystem Statistics (number of articles)

L_1	L_2	L_3	Total
2	5,991	57,360	63,353

Random Forests [23] are a machine-learning technique in which the user grows a large number of classification trees. Each classification tree is built by selecting a random number of training cases (with replacement). A subset of the available input attributes is selected at random at each node, and the best split on those attributes is used to split that node. There is no pruning, and each tree is grown to the largest extent possible. The forest is an arbitrarily large set of classification trees. Once all the trees are built, the forest makes predictions by allowing each tree to "vote" for its classification. In other words, the data are presented to each tree, which makes its classification. The output of the forest is then the classification which achieved the most votes.

Random Forests is suitable for the current ATN application as it is essentially a classification rather than a regression problem. Random Forests builds classification trees, which are used to separate data into classes. Regression trees, on the other hand, are more commonly used to predict continuous, numeric variables. Random Forests has a high level of accuracy compared to other machine learning techniques and it has efficient implementations for large databases [24].

For Random Forests, Weka defaults were retained after testing of alternatives. maxDepth was set to 0, numExecutionSlots=1, and numTrees=10.

4. Findings

4.1. Statistics

The Random Forests algorithm was evaluated for both the randomly selected articles validation set and the meta-analysis validation set on the basis of percentage of correct classifications, precision, recall, F-measure, and Area Under the Curve (AUC) [25].

Table 2. Evaluative measures.

Data set	Correct classifications	Precision	Recall	F-Measure	AUC
Random-300	71.48%	.704	.714	0.703	0.741
Meta-analysis-130	96.8%	0.969	0.968	0.968	0.924

Further visualization and evaluation work was applied to three data sets: (1) the full TAM theory eco-system, (2) the TAM-citing network, (3) and the set of L_2 articles classified as TAM-subscribing.

4.2. Multi-disciplinary Ecosystem Visualization

The complete citation data set for the TAM ecosystem (Figure 2) shows the multidisciplinary citation patterns for TAM. Visualizations were created in Cytoscape (http://www.cytoscape.org/) using the citation information, the disciplinary categorization as defined in the Excellence in Research for Australia (ERA) report (http://www.arc.gov.au/era/). The sub-code for Information systems was used to separate it from the large information and computer science domain. Thicker line weights indicate a higher number of citations between domains (or citations which reference research in the same domain). The size of the nodes indicates the relative number of articles in data set categorized into disciplines. Both node size and line width were set to be continuous. For the sake of clarity, disciplines with fewer than 50 aggregate citations to another discipline were eliminated from the figure.

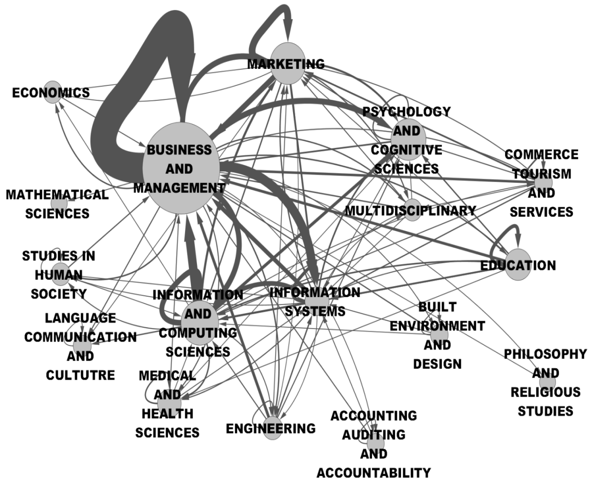

Figure 2: TAM Ecosystem

The TAM ecosystem (Figure 2) shows the multiple disciplines that are cited by articles which also reference the originating publications on TAM. Although the disciplinary categories are specific to the Australian ERA, the figure demonstrates the extent to which TAM is at the center of a large ecosystem consisting of articles from a number of non-IS disciplines which provide intellectual input and thereby shape the specific TAM theory. A manual examination of the articles showed that regardless of discipline, TAM has emerged as a preferred citation for technology studies.

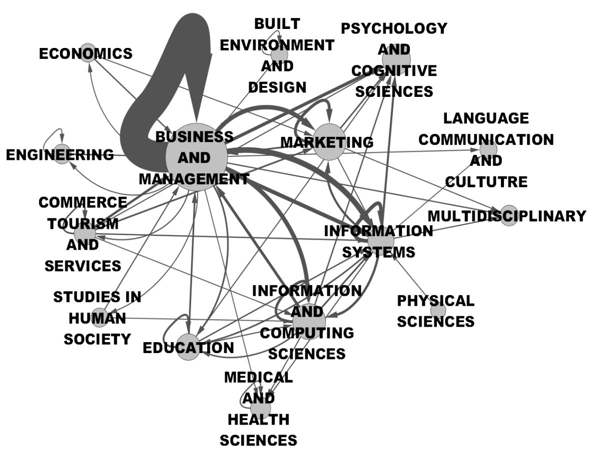

Figure 3: Articles Citing TAM

Figure 3 shows only the articles that cite TAM along with all their interconnections, with edges representing less than 10 citations removed. When compared to the entire TAM ecosystem, the extent to which the TAM ecosystem relies on the IS reference disciplines *business and management*, *marketing, psychology and cognitive sciences*, and to a smaller extent, *education* is apparent. Once only TAM-citing articles are admitted into the analysis, it is seen that IS also serves as an important source of TAM ecosystem articles that do not themselves cite TAM. Interestingly, the number of articles in the Information and Computing Sciences sub-discipline does not shrink notably when only articles citing TAM are included. This may be an indication that this sub-discipline does not provide its own reference material insofar as TAM content is concerned.

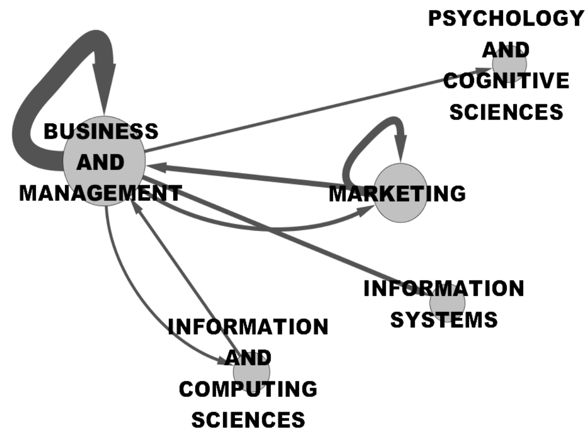

Figure 4: Random Forest Analysis of the TAM Contributing Theory Articles

The machine learning analysis (Figure 4), which contains all edges with 10 or more citations, shows the disciplines that contain articles that were predicted to subscribe to TAM. The data indicates that the core IS discipline may not be where the contributions to TAM are most likely to happen in a theory as mature as TAM. Combined, this indicates that while the contributing work for TAM may have expanded outside the IS discipline, the contributing articles still cite a core set of TAM articles inside the IS discipline.

A comparison of Figure 4 and Figure 3 indicates a number of articles (and by extension, disciplines) which invoke TAM but do not substantively contribute to the theory, in the process making it exceedingly hard to evaluate not only progress for a theory such as TAM, but the extent of continual contribution to that theory.

6. Limitations

While we consider the results reasonable as a proof-of-concept, we believe the approach has the potential to work significantly better. One reason for this is the relatively high number of MAS articles without citation records. We manually identified contributing articles which were cited in the ecosystem but that had no citation records in MAS thereby limiting the ability of the system to learn from all possible true-positive papers.

The lack of disciplinary identification of approximately 500 journals in the Excellence in Research for Australia (ERA) database also eliminated potential true positives from the analysis and thus reduced learning capacity, but was not considered to detract from the goal of this article which was to provide a proof-of-concept of one way in which the data from ADIT could be used to further understanding of a theory.

Finally, the MAS data quality was quite low in many instances forcing manual checks and eliminations of articles with completely inaccurate citation records. Future research will have to use better base data to improve the technique.

7. Concluding Remarks

This article argues for a new conceptualization of theory identity for social science based on the set of papers that are considered to contribute to the theory. While no attempt is yet made at developing rules for the integration of the set, the article proposes a general approach for the detection of the articles in the set. A machine-learning technique is developed and evaluated using the Technology Acceptance Model as a proof-of concept. Such a technique has several implications for research:

1. Major theories often require review articles to summarize progress and suggest future directions. Theory identification is a necessary component of any review in that authors must detect and examine potential contributions to a theory. Because a small fraction of articles that mention or cite a theory actually contribute to that theory, such detection is a major task because many theories now have more than 10,000 citations. The ADIT technique allows a reduction of the search space over existing approaches such as the search engines Google Scholar and Microsoft Academic Search. Identification of the publications that contribute, rather than merely invoke a specific theory will enable researchers to perform more focused and thorough reviews.
2. While not evaluated in this proof-of-concept article, it is possible that the ADIT probabilities assigned to every article in the theory ecosystem is not only an indication of the likelihood that an article subscribes to a theory, but may also reflect the relative importance of the contribution. Such attribution in the probabilities is likely because several of the features used in ADIT, such as the new Article-Level Eigenfactor measure, the Theory Attribution Ratio measure, and the Impact Factor measure evaluate the importance of contributions within the theory ecosystem. This conclusion is suggested by the considerably higher success of the algorithm in detecting the articles that had previously been included in meta-analyses and review articles.
3. This article represents a novel use of the Article-Level Eigenfactor algorithm. Our examination of the Random Forests decisions indicates that the Eigenfactor was an important feature in assigning probabilities that articles contributed to TAM. The Eigenfactor algorithm is outlined in this article, and a full description will be published separately.
4. ADIT has the potential to reduce avoidable waste in the production and reporting of research [20]. Currently, theory-based research streams contain high levels of overlapping work [26], and different theories are sometimes surprisingly redundant [7]. By simplifying the literature review process for every new article written based on a focal theory, not only is time saved, but it is more likely that researchers will succeed in finding existing work that overlaps and support their own.
5. Michie's work on the Theoretical Domains Framework [19, 27] suggests the potential for theory integration at the construct level. In addition, cross-disciplinary theory integration is supported [2, 3, 28]. Future work will likely focus on development of formal theory ontologies. For such work to be successful and have a continual impact, automatic ontology population is required [29]. ADIT represents the first technique with the potential to supply such population in the domain of behavioral theories.
6. Detection of research that contributes to a given theory has the potential to show the publication life-cycle of individual theories and for major behavioral theories as a whole. As theories mature, they may be cited but the citing paper may do so 'for the sake of it' rather than making actual contributions. The ability to detect the point at which a theory has reached its half-life may constitute an important criteria for researcher focus.

The ADIT technique introduced in this article represents the first attempt in the social sciences to develop an integrated system for theory identity detection. As it is further evolved and new features added, accuracy and usefulness can be expected to improve. ADIT is currently set up with a database and a crawler that constantly updates the database as new articles citing a theory are added to a literature database (e.g. MAS; Web of Science). The goal of ADIT is to track dozens of theories and make these theory-specific corpora available through a web portal with integrated visualizations.

Future work requires experimentation with other Machine Learning approaches, such as Artificial Neural Networks (ANNs), or Support Vector Machines (SVMs). Although these are black-box techniques, it is possible to influence their learning by making informed choices in relation to domain knowledge including architecture, error measures, and outlier definition. The goal of the ATN application is not only to classify research, but also to try to learn domain knowledge. Improved domain knowledge of the corpus of publications which identify specific theories will enable refinement of neural networks for identification of contributing publications. Domain knowledge may include specific network characteristics that represent authors or disciplines that have large number of contributing publications or the degree of citation network overlap, which indicates convergence into a single theory or divergence into competing theories. The full potential of ADIT will be seen only when multiple theories are added and examined. Once the ecosystems, theory-citing articles, and contributing articles for multiple theories are available, overlaps between theories may be empirically evaluated to further our understanding of theory creation and transfer between disciplines. It has been argued that whereas contributions to theory remains a linear process, researcher inability to integrate the results increases exponentially [9]. ADIT has the potential to alleviate these problems.

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