Wide-scale Automatic Analysis of 20 Years of ITS Research

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Abstract. The analysis of literature within a research domain can provide significant value during preliminary research. While literature reviews may provide an in-depth understanding of current studies within an area, they are limited by the number of studies which they take into account. Importantly, whilst publications in hot areas abound, it is not feasible for an individual or team to analyse a large volume of publications within a reasonable amount of time. Additionally, major publications which have gained a large number of citations are more likely to be included in a review, with recent or fringe publications receiving less inclusion. We provide thus an *automatic methodology for the large-scale analysis of literature within the Intelligent Tutoring Systems (ITS) domain*, with the aim of *identifying trends and areas of research* from a corpus of publications which is significantly larger than is typically presented in conventional literature reviews. We illustrate this by a novel analysis of 20 years of ITS research. The resulting analysis indicates a significant shift of the status quo of research in recent years with the advent of novel neural network architectures and the introduction of MOOCs.

Keywords: Topic Modelling, Epistemological Engines, Automatic Literature Survey.

1 Introduction

The considerable volume of research within Intelligent Tutoring Systems (ITS) presents challenges to the quantification of the various fields present within the domain. Conventional literature surveys are typically performed using manual analysis and filtering of available literature and as such are limited in the volume of publications. Additionally, researchers may fail to account for research, which is niche, but may be still important. Surveyors are furthermore likely to include main-stream research only, or research assisting in their argument. Thus, we propose to leverage the novel topic modelling algorithm Top2Vec [1] for the analysis of a large volume of ITS research. Advantages to such an analysis include the volume of ITS research processed, which exceeds that which may be feasible by even a large team of contributors. Additionally, the speed of topic analysis ensures ample time for the further analysis of temporal factors within the corpus and presentation of relationships between any identified topics.

Major contributions of this work are: 1) automatically identifying, for the first time, significant trends in ITS (e.g., temporally, ITS has observed a significant shift in research popularity from Adaptive Hypermedia towards online MOOC platforms; applied architectures and algorithms have shifted significantly towards Deep Learning and applications of Neural Networks); 2) automatically extracted relationships between several ITS topics indicate potential for novel areas of research; 3) we demonstrate the power of the recent Top2Vec algorithm to assist, for the first time, in large scale literature analysis, without limitations presented by conventional probabilistic topic models. Compared to existing studies within ITS, this research provides a *unique overview of the last 20 years of research*, without the bias presented by human-reviewers who may, arguably, 'cherry-pick' studies to argue their point. Our research accounts for *all research made available by API resources*.

2 Related Works

Traditional literature surveys in ITS follow a manual process, where identified publications are filtered, resulting in a significantly smaller batch of publications used in the final review. ITS reviews, such as [2], apply a Systematic Literature Review process. They analysed a total of 33 publications, filtered down from an initial corpus of 4,622 papers. These resulting papers are analysed in-depth; however, the exclusion of such a large volume of papers clearly indicates missed opportunities for obtaining insight from the excluded publications. Outside of manual literature surveys, we identified [3], which performed analysis of a larger volume of publications on a quantitative level. The scope of the publication addressed barriers and trends of ITS adoption rather than the trends and relations of the overarching field.

Top2Vec [1] provides a very recent alternative to Bayesian topic models such as PLSA and LDA [4, 5], eliminating the need for pre-defining the topics number and filtering stop words. It leverages language embeddings and enables pre-trained language models to be applied via Doc2Vec [6], BERT [7] or Universal Sentence Encoder [8]. A semantic embedding of joint document-word vectors is generated where the distance between document and word vectors represents semantic association. This ensures that semantically similar documents achieve a smaller distance between each other when compared to dissimilar documents. Resulting embeddings are clustered using the HDBSCAN [9] algorithm into topic clusters, with the hierarchical nature of HDBSCAN ensures automatic identification of the topic number. Given the high dimensionality of document embeddings, clustering requires prior dimensionality reduction through the UMAP [10] algorithm. Top2Vec has been demonstrated to outperform LDA and PLSA when applied to the benchmark 20NewsGroups [11] dataset [1].

3 Corpus Generation

3.1 Data Collection

We performed collection of publication data from the ITS domain via several API resources, over the past 20 years. These consist of the arXiv Preprint Repository, Springer API, SAGE API, Elsevier API and CORE API [12, 13, 14, 15, 16]. We selected query terms based upon a sample of the key phrases presented in the 2000-2020 ITS Conference Proceedings; however, we avoided inclusion of low-level specific terms, to ensure the resulting document distributions were unbiased. To be comprehensive, we collected literature not limited to journals and conferences, but also included book chapters, preprints and academic theses. In total, we collected 5018 documents from 2000-2020. Research from 2000-2020 was selected to provide a wider-scale analysis, beyond that of only the most recent literature, which could assist in evaluating the changes in long-term trends of ITS quantitatively.

Following the collection of raw publication data, it was necessary to filter out results which were not relevant to ITS using Boolean word matching at the abstract level. Given that some terms used within ITS (e.g., adaptive learning) may be confused with general machine-learning terms by a partial matching system, it was deemed necessary to apply absolute string-matching during filtering. Documents were excluded if they failed to contain any instances of the terms within our search query. Given the large volume of research identified, it was necessary to perform this automatically with regex.

3.2 Preprocessing

We performed no preprocessing of the corpus prior to topic analysis, with the aim of maintaining contextual information within generated embeddings. Stop word removal, lemmatisation or stemming was not necessary as detailed by [1], in contrast to LDA, where stop word removal and additional filtering of highly frequent terms may be performed [17] to improve model performance. Language-checks were performed on the corpus to remove any non-English publications, which could impact model performance. For this we applied the langdetect [18] Python library. Following filtering of non-relevant results, the corpus size was of 3898 documents abstracts and titles, which we combined for our analysis. Given the limitations of access to publications, we were only able to collect abstracts, as access to full-text results was limited.

4 Analysis

The methodology for our analysis involves the modelling of topics within our corpus using the Top2Vec algorithm [1] and the subsequent analysis of the resulting topics in relation to temporal range and relationships between topics. Our work is available at[1].

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[1] *https://github.com/ryanon4/epistemological-topic-modelling*

4.1 Topic Modelling Approach

Top2Vec identifies semantic relationships through learning of a distributed representation via the Doc2Vec algorithm [6]. Alternatively, pretrained models may be applied including Universal Sentence Encoder [8] or the BERT [7] transformer network. However, our experiments identified that Doc2Vec embeddings fine-tuned to our corpus outperformed these, likely due to the presence of frequent domain-specific language within ITS research. Additionally, the resulting clusters may be visualised to provide an understanding of clustering results as presented in Fig. 1.

HDBSCAN labels a portion of the documents within our corpus as noise, which we removed prior to presentation in Fig. 1, leaving all topics without any noise present. Given that ground truth labels were not available for clustering evaluation, we applied Silhouette scoring [19] using Euclidean distance and achieved a score of 0.37 when accounting for all 33 topics. When reducing this to only account for topics relevant to ITS, this increased to 0.42. In total HDBSCAN identified 33 separate topics.

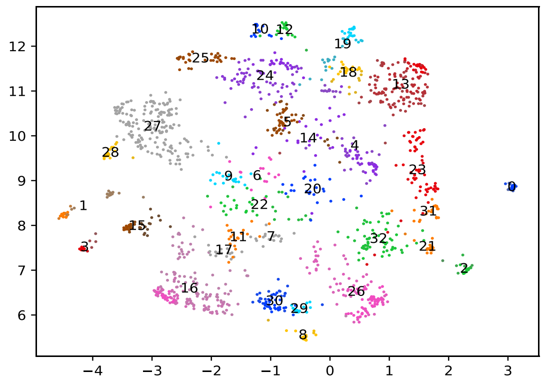

Fig. 1. Clustering Results following noise removal with topic labels assigned

For higher accuracy, we further performed manual evaluation of the resulting topics at a qualitative level and filtered non-relevant topics which may have arisen, to ensure that only those relevant to ITS remain. Filtering consisted of analysis of the topic-word distributions for each topic, and exclusion was performed when a significant level of noise or non-informative terms were identified. A label was manually assigned to relevant topics, based upon the word distributions they entailed. These are detailed in Table 1.

Resulting topics indicate 11 highly coherent and relevant topics out of the 33 topics identified by Top2Vec. Topics were excluded where word-distributions contained unrelated terms and could not be clearly labelled, or the distributions were related, however contributed less to our analysis. Removal of non-relevant documents and noise reduced the total corpus size for our analysis to 1223 documents. Topic 13 indicates the types of architectures and models present within research and as such does not serve as a useful topic label for the corpus. We investigated this separately via a temporal analysis in section 4.3.

4.2 Topic Analysis

Results from topic modelling with Top2Vec identified a range of ITS relevant topics within our corpus which we present ordered by the size of each identified topic in Table 1. These range from high-level areas which may entail different approaches within, to specific areas of research relevant to ITS. Of the identified areas, high-level topics correlate to a larger volume of entailing documents with specific topics containing a lower volume of documents. The clustering of publications using the HDBSCAN algorithm leads to the assigning of single topic labels to each document, meaning that unlike probabilistic models like LDA, documents may not belong to multiple topics and therefore more specific or low-level topics typically contain fewer documents. Within this section we ensure that all references are made using publications present within our corpus. Given the criteria applied during data collection, research discussed may include preprint or thesis research which has not been peer-reviewed.

Table 1. Identified Topic-Word Distributions by Top2Vec, Topics Deemed relevant to ITS by Qualitative Analysis

Topic Terms	Topic ID	Topic Label (Manually-Determined)
Hypermedia, aeh, aehs, ims, adaptive, adaptation, adaptivity, navigation, personalization, links, specification	0	Adaptive Educational Hypermedia
Dialogue, tutoring, natural, intelligent, language, tutorial, automatically, conversational, apos, corpus, medical, quot	2	Intelligent Dialogue Systems
Agent, animated, emotion, affective, emotional, pedagogical, agents, emotions, facial, conversational, apos	5	Pedagogical Agents
Moodle, lms, source, management, open, centre, lectures, platforms, basic, dashboards, assignments	7	Learning Management Systems
Peer, assistance, collaborative, conditions, learned, tutor, collaboration, dialogue, actions, cscl	8	Computer-Supported Collaborative Learning
Moocs, massive, mooc, dropout, forum, open, engaging, courses, videos, rates	12	MOOCs
Bayesian, networks, fuzzy, logic, artificial, diagnosis, intelligence, intelligent, neural, tutoring	13	Machine Learning Model Types and Algorithms
Simulations, simulation, intelligent, animated, virtual, training, multimedia, agents, reality	14	Simulations
Games, game, serious, play, agent, interact, intelligent, bring, initiative, metrics, simulation	17	Gamification
Essay, scoring, essays, automatic, grading, writing, automated, English, language, neural	19	Grading and Assessment Scoring
Recommender, recommendation, personalization, links, personalized, java, hypermedia, experiments, lecture, adapting	28	Recommender Systems

Topic 0 – Adaptive Educational Hypermedia

This topic represents the high-level area of Adaptive Educational Hypermedia Systems (AEHS). These may be defined as adapting content to fit the goals and needs of a user or student [20]. Documents within our corpus labelled under this topic typically investigate web-based approaches for adaptive tutoring [21] and relate closely to other ITS areas including Learning Management Systems (LMS) and MOOCs. We identified several approaches involving neural networks of which [22][23] [24] are a sample, as well as framework proposals for the building of e-learning platforms [25] [26].

Topic 2 – Intelligent Dialogue Systems

Intelligent Dialogue Systems (IDS) typically investigate the application of conversational agents, applied to assisting in the pedagogical process. Sample documents involve the application of conversational agents to address tutoring of concepts and principles with students for both physics and programming [27] [28].

Topic 5 – Pedagogical Agents

We identified considerable interest in research related to the impact of pedagogical agents [29] [30] [31] [32] and how the presentation of these agents may impact success within ITS. Other documents more closely correlate to emotion recognition through the assessment of learner feedback [33]. Adaptation of pedagogical agents in response to emotional queues are frequent within this topic [34], however research may alternatively investigate the impact of perceived emotions of pedagogical agents [35].

Topic 7 – Learning Management Systems

This topic entails the high-level area of Learning Management Systems. Within this topic, a significant volume of research relates to e-learning platforms such as Moodle [36] and includes proposals for the modification of such platforms to adapt to user learning styles and requirements. Interestingly, the majority of publications present within this topic avoid architectural specifications or computing-based terminology, and instead typically provide case studies of the implementation of existing LMS.

Topic 8 – Computer Supported Collaborative Learning

Documents assigned to this topic generally relate to Computer Supported Collaborative Learning (CSCL). Relations within this area include pedagogical agents [37], although generally there were fewer instances of bridging between the identified topics.

Topic 12 - MOOCs

Massive Open Online Courses (MOOCs) are a relatively recent aspect of ITS research, and we identify our earliest instance of this within our corpus in 2013 [38]. We identify 38% of research in this topic entailing learning analytics [39] [40] [41], which involves the wealth of data provided by MOOC platforms. This data may be applied to dropout prediction and forecasting of MOOC platforms [42] [43], and we identify 11% of documents involving dropout prediction.

Topic 13 – Architectures and Algorithms

Documents assigned to this topic are more closely associated with implementation and architectures of models than ITS processes. We identify applications of fuzzy logic [44] [45] [46] comprising 25% of the topic, with 11% discussing or applying neural networks [47] [48] and 8% through clustering [49]. Given that algorithms and architectures will be likely present in the wider corpus we perform a temporal analysis of the entire corpus in section 5.3.

Topic 14 - Simulations

This topic represents research involving the simulation of learning environments and simulated agents. We identify articles relating to pedagogical agents [50], CSCL [51] and adaptive hypermedia [52] within this topic. While documents relate to other ITS areas the majority discuss the simulation of environments to assist with learning. Instances of simulation include resource allocation training for police forces [53] and the use of virtual reality simulated environments [54] [55].

Topic 17 - Gamification

Publications applying gamification within ITS fall within this topic, with research contributing to the use of game mechanics for positive educational outcomes. Games may be applied to assisting learning in STEM subjects [56] [57] within virtual learning environments or in the tutoring of programming [58].

Topic 19 – Grading and Essay Scoring

This topic relates to the grading of work with ITS and is most directly associated with the area of Automatic Essay Scoring (AES), however other areas of grading exist within the topic. We identify 42% of documents discuss essay scoring directly, with research investigating short question grading [59] and essay scoring [60][61]. The grading of text is not the only research within this topic however, and we identify unpublished research in the automated grading of map sketches [62] within our corpus sample. Within this topic we identify 18% of publications applying neural networks, while 6% apply ontologies and 5% applying Bayesian learning.

Topic 28 – Recommender Systems

Documents relating to recommender systems comprise this topic, which is the smallest relevant topic identified by our analysis. Research within this area present systems for the recommendation of courses in MOOC platforms [63] and adaption of learning environments using recommender systems [64] amongst others. This topic can be closely linked to several of our identified topics including adaptive educational hypermedia, computer supported collaborative learning and MOOC systems.

4.3 Temporal Analysis of ITS

We visualise the changes in resulting topics from our analysis in Fig. 2. These are normalised per-year to eliminate influence by changes in yearly publication volume.

Resulting temporal distributions generally correlate to the sizes of our identified topics, with documents assigned to Adaptive Educational Hypermedia forming the largest portion of research from 2001-2015. Other topics outside of these generally fail to form more than 20% of research interest prior to 2016, where research into MOOCs overtakes other topics to become the most dominant topic within our corpus. This considerable change in interest towards MOOC platforms may be influenced by the wealth of data obtained and provided by such platforms, with public datasets such as [65] allowing researchers easy access to data to contribute to the field, and the general trends towards 'Big Data' application and research. A decrease in popularity of AEH, IDS and several other topic types may further contribute to the adoption of MOOC type research, which may provide more easily accessible datasets and feature ranges.

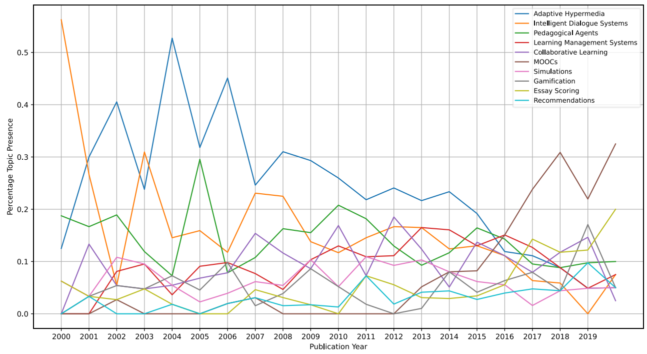

Fig. 2. Temporal Changes in Topics from 2000-2020. Normalised by number of publications each year

We present the occurrences of different algorithms and architectures in Fig. 3. Results indicate the consistent presence of ontologies within research throughout 2000-2020, while applications of other algorithms identified by Top2Vec fluctuate in popularity. Most notably, an increase in presence of both clustering and neural networks is observed from 2010-2020 within the entire corpus. In recent years (2019-2020), the volume of research discussing neural networks increases considerably. This may indicate the general trends of the wider computing field and may be attributable to recent novel algorithms such as the transformer network and BERT [7].

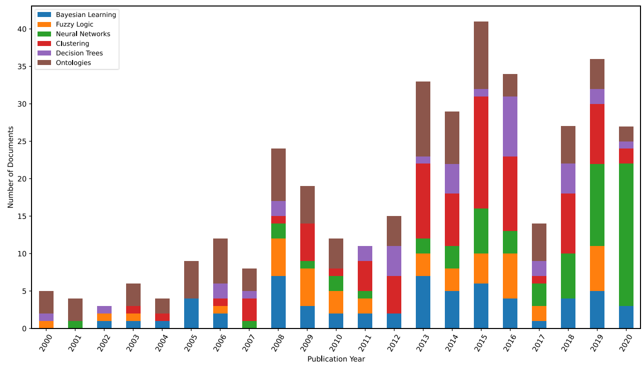

Fig. 3. Algorithmic and Architectural Presence based upon Publication Year.

4.4 Topic Graph Relationships

For further analysis, we construct a network of relationships between ITS topics, as depicted in Fig. 4. These are constructed using the cosine similarity between average document embeddings of each topic. Average document embeddings were generated using the Doc2Vec document embeddings of all documents assigned to a topic by Top2Vec. We assign connections between topic nodes using the three highest scoring similarity relationships for each topic.

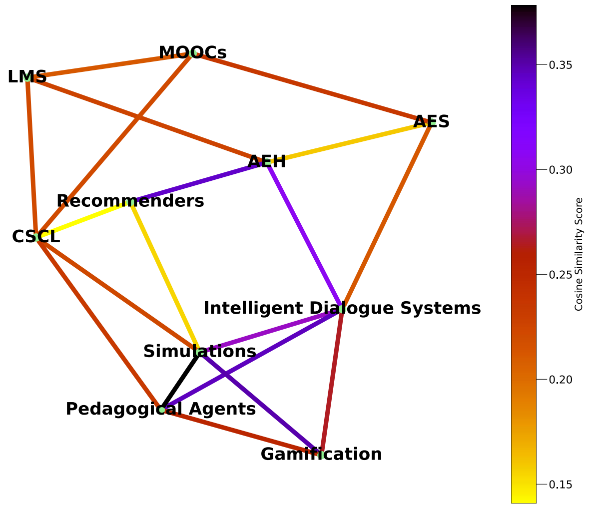

Fig. 4. Relationships of Relevant Topics based on Cosine Similarity between Average of Topic Vectors.

Relations between Pedagogical Agents, Simulations, IDS and Gamification reflect the links present within the corpus, where agents may be presented to users in a graphical manner. The cosine similarity scores between these four topics are the highest within the network and demonstrate the linking themes and interoperability that these areas present. In the case of AEH and Simulation, research investigating the adaptation of simulated agents in response to user or student is present within both topic corpuses. Further high scoring similarities are observed between AEH and Recommender Systems, wherein publications may discuss the adaptation of recommender systems dynamically, based upon user responses and performance. Given that recommender systems may be closely attributed to adaptation of systems to user input, we argue that this is represented through the association with Adaptive Hypermedia (AH) and Learning Management Systems (LMS) through the recommendation of course content.

LMS is additionally closest associated to CSCL and MOOC systems. We argue that LMS and MOOC systems are by nature closely linked (with MOOCs forming a subset of LMS) and therefore documents within these topics may share semantic terms. Both LMS and MOOC systems research incorporate aspects of collaborative learning within our corpus. A link between MOOCs and Automated Essay Scoring research is present, being the strongest link for AES, which is one of the weakest scoring topics, in terms of cosine similarity with other topics. This reflects how many of the topics present within the corpus offer a degree of interoperability, which is less so in the case of AES.

5 Discussion and Conclusion

The application of the novel Top2Vec [1] algorithm to topic analysis of the ITS literature enables an overview of the development as well as current research field. Contrary to well-known approaches, such as LDA [5], the algorithm requires fewer preprocessing steps and therefore demonstrates potential in application to a range of epistemological research without expert knowledge. Furthermore, this analysis approach ensures a significantly higher volume of research can be processed and analysed compared to manual review types. Our analysis of the resulting topics identified contributes to an understanding of the relationships between topics and the volume of research various areas contain.

General findings from our investigation indicate research involving Adaptive Hypermedia to comprise the highest volume of research overall. This area presents a high level of interoperability with others, such as with research applying Simulation and Recommender Systems in an adaptive manner, based on user input. Temporally, Adaptive Hypermedia entails the largest portion of ITS research up until 2016, where it is overtaken by MOOC research. Given that our analysis accounts for all research from 2000-2020, there exists further opportunity for a dedicated analysis of the more recent years publications only, in order to form a better understanding of reasons for MOOC research popularity, and identification of potential new areas of research within. Topics such as Automatic Essay Scoring are clearly underrepresented and may deliver promising avenues of future research – especially as some of this research seems yet unpublished. Temporally, we identify a shift in research in recent years (2016-2020) with a considerable increase in interest of MOOC systems, and applications of neural network architectures to research within these years. This, we argue, is likely the result of the increase in availability of data generated by MOOC systems, which achieve a considerable throughput of users and therefore volume of data. In the case of applications of neural network, we argue the interest spike follows the considerable improvements made in recent years for transformer-based and pre-trained networks. As a final note on our methodology, we identify limitations in the applications of abstracts only within our corpus, whereas structured full-text data may have provided valuable insight into topics of separate sections (e.g., related works, methodologies). We are considering analysing specifically further research targets in papers, both temporally, to understand to which extent the targets have already been reached, or if they are open, as well as in terms or recent year gaps to fill. Key phrases for our search were based on the ITS Conference only. This may be a limitation, and other possible variations could be considered. However, given that the extraction was over the last 20 years, so conforming exactly to our target time period, we can say with some confidence that these results clearly show the progress of ITS research during the past 20 years from an ITS conference perspective.

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