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Yadav, Neha
Department of Computer Science Engineering/Information Technology Jaypee Institute of Information Technology

Gopinathan, Dhanalekshmi
Department of Computer Science Engineering/Information Technology Jaypee Institute of Information Technology

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Graph Based Analytics and Review of Knowledge Graph Field by Using Two Decade Data- Finding Paradigms and Opportunities

Neha Yadav[1]*, Dhanalekshmi Gopinathan[1]
[1] Department of Computer Science
Engineering/Information Technology
Jaypee Institute of Information Technology, Noida

E-mail: *nehayadav9506@gmail.com, Dhanalekshmig@gmail.com

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Abstract: Knowledge Graph Embedding (KG Embed) has an important role in extracting the query and retrieving the required information in the technology specifically in scientific research. A surge is seen in the growth of knowledge graphs and also in knowledge representation and reasoning. This paper with the help of the knowledge graph creation helps in finding the hottest topic for research, Specifically, this study includes four research repositories that are Google Scholar (GS), IEEE Xplore, Science, and Worldwide Science (WWS). This study is based on keyword searching, which includes four keywords that are Knowledge graph (KG), Knowledge graph embedding (KG Embed), Recommendation system knowledge graph (RS KG), and Recommendation system in the education domain (RS in education). The data of several papers, articles, and books present in these four repositories from 2000 to 2022 is collected using these four keywords. After this, the paper visualizes this data using graphs and knowledge graphs with the help of parameters like centrality and clustering, which shows that Google Scholar contains more data than other repositories and the hottest topic in research is knowledge graph. It also gives an overview of how a knowledge graph is used in the recommendation system and how it is helpful. Based on the result that we got through the visualization of graphs and knowledge graphs; this study summarizes the suggestions and directions for researchers and practitioners to do future research on knowledge graphs by keeping all the related studies and points. This research takes into account the knowledge Graph research papers, articles, books, and theses from these four sources.

Keywords: Knowledge Graph Embedding (KG Embed); Recommendation System Knowledge Graph (RS KG); Graph Based Analytics; Knowledge Graph.

1. Introduction

Semantic knowledge bases like knowledge graphs play a key part in shifting big data to big Knowledge data. A knowledge graph (KG) is a kind of special database where information is structured in a way that it can generate, store, and search for knowledge. The knowledge graph acquires and integrates the information into ontology which leads to creating new knowledge by applying it to reason [1]. It has been applied in many intelligent systems and has drawn a lot of research interest. The knowledge graphs have been applied to many different types of tasks like link prediction, recommendation, natural language processing (NLP), question answering, knowledge management, and entity linking [5]. The knowledge graph had its foundation laid in mid-2019 when Google invented the knowledge graph in 2012. It is a database of a large collection that is gathered from different sources such as DBpedia [4], Wikipedia [2], Wordnet, and Schema [7] structured data like Facebook, Twitter, etc. Today, Knowledge graphs have been used extensively in anything from search engines, chatbots, product recommenders, and autonomous systems [3, 11, 12]. Knowledge graphs complement machine learning techniques to reduce the need for large, titled datasets, facilitate transfer learning, and explain and encode domain, task, and application knowledge that would be costly to learn from data alone [8, 9, 10]. A knowledge graph organizes and integrates data according to an ontology [13, 15], which is called the schema of the knowledge graph, and applies a reasoner to derive new knowledge.

However, given the rapid development of knowledge graphs in recent years, earlier studies cannot accurately reflect the current state of the knowledge graph domain [6]. Furthermore, prior studies were largely exclusively focused on the field of library and information science, ignoring the creation and implementation of knowledge graphs in the field of computer science [22]. Knowledge graphs can be created from scratch, e.g., by domain experts [69], learned from unstructured or semi-structured data sources, or assembled from existing knowledge graphs [70], typically aided by various semi-automatic or automated data validation and integration mechanisms [23, 24]. AI applications that include knowledge graphs have very rich information [28], which strongly supports the applications [26]. In the research field, the knowledge graph is quite popular, it is seen by the results [71] that are achieved by this study of keyword searching and knowledge graph creation [27].

This study compiles the foremost recent knowledge graph literature; the knowledge obtained aids in illustrating the research trend and hot themes within the field [29, 30]. To demonstrate this, the paper first defines the notion of a knowledge graph, before examining the research progress and topic evolution of knowledge graphs in scientific articles from four leading research repositories (Google Scholar (GS), IEEE Xplore, Science, and World Wide Science (WWS)) from 2000 to 2022.

So far, only one or two repositories have been considered for the study portion of the knowledge graphs in the existing literature [32]; the repositories that are referred to are a Web of Science and SCI-Expanded [72]; however, in this paper research articles from four repositories are reviewed, and compared.

The main contribution of this paper includes:

- The recent trends in the Knowledge graph research field and visualizes the number of scientific articles found in this field from 2000 to 2022.
- This study also provides the trends of the articles and major areas/regions/countries that give more contributions to this field.
- It also gives the publication resources, subjects, major topics, and suggestions on future directions.
- The organization of the rest of the paper is as follows. Section 2 gives a tour on the literature survey of the topic. Section 3 provides a brief introduction and applications of the
- Knowledge graph. Section 4 explains the proposed framework to get the recent trends in knowledge graph research. Section 5 depicts the experimentation and result analysis and section 6 summarizes the work done in this paper. Finally, section 6 lays the groundwork for future projects.

2. Literature Survey

This section reviews the trajectory of research in Knowledge graph visualization [73] throughout the past several decades, ranging from early work targeted at novices to automation and modular design [34, 35]. The literature survey for performing this study is summarized in Table 1 and Table 2 below:

Table 1: Comparative Study of Previous Published Work-Based on Methodology

Authors	Year	Title	Proposed work	Methodology used
Li, Manling, et al., 2018 [1]	2018	Link Prediction in Knowledge Graphs: A Hierarchy-Constrained Approach	Proposed a link prediction method based on hierarchy-constrained called hTransM.	hTransM
Hogan, A., Blomqvist, et al., 2021 [31]	2021	Knowledge graphs	Gives a comprehensive overview of the knowledge graph.	No methodology used
Zhang, Z., Cao, L., et.al., 2020 [14]	2020	Representation learning of knowledge graphs with entity attributes.	Presented a novel method for representation learning which uses the attribute information of entities.	Attribute-embodied Knowledge Representation Learning (AKRL)
Li, G., Wang, Z. and Ma, Y., 2019 [16]	2019	Combining domain knowledge extraction with graph long short-term memory for learning classification of Chinese legal documents.	By using Graph LSTM a method is proposed for learning Chinese legal document classification combined with domain knowledge extraction.	XML
Bloem, P., Wilcke, X., Berkel, L.V. and Boer, V.D., 2021 [17]	2021	kgbench: A collection of knowledge graph datasets for evaluating relational and multimodal machine learning	Introduced new benchmark tasks on RDF-encoded knowledge graph.	Pytorch
Song, H.J., Kim, A.Y. and Park, S.B., 2020 [18]	2020	Learning translation-based knowledge graph embeddings	This paper presents an N-pair translation loss that at one	Translation methods

		by N-pair translation loss.	update considers multiple negative triples.	
Kazemi, S.M., Goel, R., Jain, K., Kobyzev, I., Sethi, A., Forsyth, P. and Poupart, P., 2020. [19]	2020	Representation learning for dynamic graphs: A survey	This paper presents a framework of encoder-decoder for dynamic graphs in representation learning.	RNN
Zhu, X., Li, Z., Wang, X., Jiang, X., Sun, P., Wang, X., Xiao, Y. and Yuan, N.J., 2022. [20]	2022	Multi-Modal Knowledge Graph Construction and Application: A Survey.	This paper gives a systematic review of multi-modal knowledge Graphs.	Multi-modal Knowledge Graphs.
Lin, J., Zhao, Y., Huang, W., Liu, C. and Pu, H., 2021. [21]	2021	Domain knowledge graph-based research progress of knowledge representation	The paper gives a survey on domain-based knowledge graphs and also gives the development of knowledge graphs based on different factors.	Medical domain used.
Al-Moslmi, T., Ocaña, M.G., Opdahl, A.L. and Veres, C., 2020. [25]	2020	Named entity extraction for knowledge graphs: A literature overview	The paper gives an overview of Named entity linking, Recognition, and Disambiguation.	GERBIL
Cao, Z., Xu, Q., Yang, Z., Cao, X. and Huang, Q., 2021, May [33]	2021	Dual quaternion knowledge graph Embeddings	The paper gives the study of the problems in the learning representations of entities and relations of the knowledge graph that will be used for link prediction tasks.	Method used is- DualE.

Table 2: Comparative Study of Previous Published Work

Authors	**Title**	**Result**	**Merit**	**Demerit**
Li, Manling, et al., 2018 [1]	Link Prediction in Knowledge Graphs: A Hierarchy-Constrained Approach	This paper determines a marginal adaptively which can achieve optimal predictive performance.	The margin modeled is based on the hierarchical structures that contribute to the optimal single and multi-step margin.	Other margin-based translation methods can be used and compared with each other to show which is the best among them.
Hogan, A., Blomqvist, et al., 2021 [31]	Knowledge graphs	It gives a comprehensive overview of knowledge graphs; models are also discussed with techniques and also presents some future directions.	The paper has discussed models with the help of that data can be structured, validated, and queried as graphs. Some techniques are also discussed for inductive knowledge over graphs.	The paper didn't discuss any implementation part of the knowledge graphs with the review part to show how it can connect with the review.
Zhang, Z., Cao, L., et.al., 2020 [14]	Representation learning of knowledge graphs with entity attributes.	The AKRL model performs the best in attribute information processing.	The AKRL model provides a new way to use a convolutional neural network for the dataset with a larger number of relation triples.	The method is limited to the three layers only, limiting the pattern recognition ability. Semantic knowledge representation and information acquisition need to improve.
Li, G., Wang, Z. and Ma, Y., 2019 [16]	Combining domain knowledge extraction with graph long short-term memory for learning classification of Chinese legal documents.	The proposed method has an over 90% rate of accuracy, it improves the classification accuracy	In the paper text features are extracted that are based on the domain ontology model and they are converted into vectors, which is helpful in reducing the dimensions and it has a strong feature representation.	The other Classification methods need to be explored based on the semantic analysis.

Bloem, P., Wilcke, X., Berkel, L.V. and Boer, V.D., 2021 [17]	kgbench: A collection of knowledge graph datasets for evaluating relational and multimodal machine learning	This paper includes primarily node classification tasks on RDF-encoded knowledge graphs, which also support images, video, and audio.	This paper gives a modest ontology so that it can support audio, video, and images by expressing these datatypes in the form of binary-encoded string literals.	The graphs considered are small so they will provide a relatively small image of the real-world knowledge graphs.
Song, H.J., Kim, A.Y. and Park, S.B., 2020 [18]	Learning translation-based knowledge graph embeddings by N-pair translation loss.	This paper proposed a new loss function for translation-based knowledge graph embeddings.	The loss function proposed can receive multiple negative triples per positive.	Cross-domain functionalities can be added for further development of visualization.
Kazemi, S.M., Goel, R., Jain, K., Kobyzev, I., Sethi, A., Forsyth, P. and Poupart, P., 2020. [19]	Representation learning for dynamic graphs: A survey	This paper presents a framework of encoder-decoder for dynamic graphs in representation learning.	This paper gives information about various learning and reasoning with dynamic graphs. This paper also shows the directions to improve the reasoning and learning of dynamic graphs.	This survey is only findings based no implementation is present to justify the findings.
Zhu, X., Li, Z., Wang, X., Jiang, X., Sun, P., Wang, X., Xiao, Y. and Yuan, N.J., 2022. [20]	Multi-Modal Knowledge Graph Construction and Application: A Survey.	This paper gives a systematic review of multi-modal knowledge Graphs.	This paper presents a systematic review of opportunities and challenges in the construction and applications of MMKG with weaknesses and strengths of solutions.	The research survey ended with open problems of MMKGs. And the implementation of weakness findings is not done.
Lin, J., Zhao, Y., Huang, W., Liu, C. and Pu, H., 2021. [21]	Domain knowledge graph-based research progress of knowledge representation	Gives an overview of different domain-based knowledge graphs, and their construction on the basis of different parameters.	The paper has given great information about domain-based knowledge graphs, the paper also shows the study findings of domain knowledge graph creation on different parameters like entities, properties, and relationships.	They provide future trends, but no information on how to overcome the problem we are facing in recent domain-based knowledge graph creation.
Al-Moslmi, T., Ocaña, M.G., Opdahl, A.L. and Veres, C., 2020. [25]	Named entity extraction for knowledge graphs: A literature overview	The paper provides an overview of recent advances that are used in the central task for uplifting the NL texts to Knowledge graphs.	This paper provides the approaches that are involved in NER methods that help in NL information available for Knowledge Graphs as computer processable.	The paper doesn't provide an overview of relations between entities in Natural Language that can't restrict it to named entities.
Cao, Z., Xu, Q., Yang, Z., Cao, X. and Huang, Q., 2021, May [33]	Dual quaternion knowledge graph embeddings	This paper proposed a new method named DualE (dual quaternion knowledge graph embedding) which gives dual quaternions into knowledge graph embeddings.	The DualE is the first unified Framework that helps in embracing both rotation and translation-based models. The other merit is it expands the embedding space with more geometric and physical interpretation.	Only two Datasets are used for comparisons, at least three or four should be used so that the method will give a unified framework.

3. Knowledge Graph

The Knowledge Graph (KG) is a graph-based representation of knowledge [36], where nodes of the graph represent entities of interest and edges represent relationships [37, 38, 40]. Entities are titled with attributes and edges capture relationships among them. Entities can be events, real-world objects [39], and situations whereas the relationships can be links [41] between the entities [42, 50]. For example, the statement "Martin is a friend of Josh and both are interested in hiking". The knowledge graph corresponding to the above statement is depicted in Fig. 1. The events/entities in the above statements are Martin, Josh, and Hiking which are represented as three nodes in the graph shown in Fig.1. The relationships between these nodes are represented by the titled edges in the graph [43]. The construction of the knowledge graph is shown with this simple graph, After the construction, where these knowledge graphs are used [44], they are used in various research fields [45], recommendation systems [46], and also in Natural language processing [51, 53].

Some real-life examples are explained below:

- Question-Answering: A Knowledge graph containing a wealth of information and question Answers [47] are a good way to help end-users more effectively [54] and also more efficiently retrieve information from the knowledge graph 48).
- Storing information about research
- Recommendation system: It helps in finding relationships between movies, TV shows, and people like [49] on Netflix.
- Supply chain management: Companies can easily keep track of inventories [52] of different components, times, etc.
- Linking data is an active research domain that aims to establish semantic links between entities described in different datasets [60].
- The knowledge graph is used to improve the search relevancy of Google [61].
- The knowledge graph presents boxes [55] with search results that are targeted to provide exact and directed answers to what [62] the users search for or what the search results are closely related to [56]. For example, if search for any country, then the result will be a country or a person with a country name like India is some cricket player's daughter's name and also the country name so the search query will have two relative results [74].

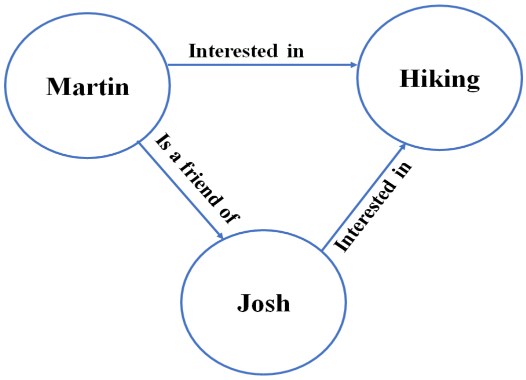


Fig. 1: Working model of Knowledge Graph Representation.

The real-life scenario of one of the applications is explained in Fig. 2. As Fig. depicts the user opens Google Assistant and with the help of a voice command [75] the user searches for some content like information about the "knowledge graph" [63]. The search query will run in the backend and collect data from the database [57, 58, 59]. The data in the database is from different sources these sources are connected through knowledge graphs [64]. So, all information from different sources will be shown on the Google Home page [65] suggesting information about the knowledge graph [66]. The next section explains the proposed framework for gathering the recent trends in the Knowledge graph research field for the number of scientific articles found in this field and the major areas/regions/countries that contributed more to this field [67].

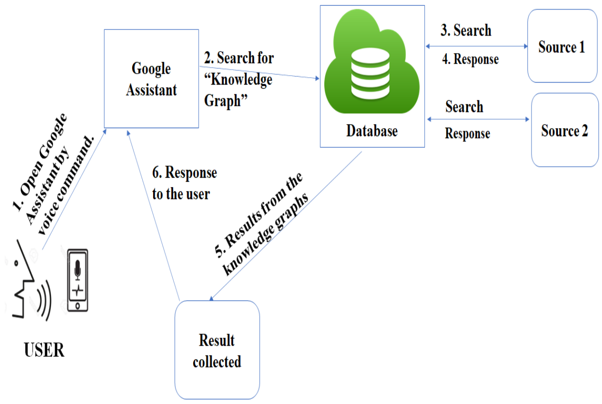


Fig. 2: Flow of Knowledge Graph Application

4. Proposed Methodology

The proposed methodology- Query Analysis of Knowledge Graph consists of four phases which include, Data source, Data filtering, construction of knowledge graph, and Data analysis as shown in Fig. 3.

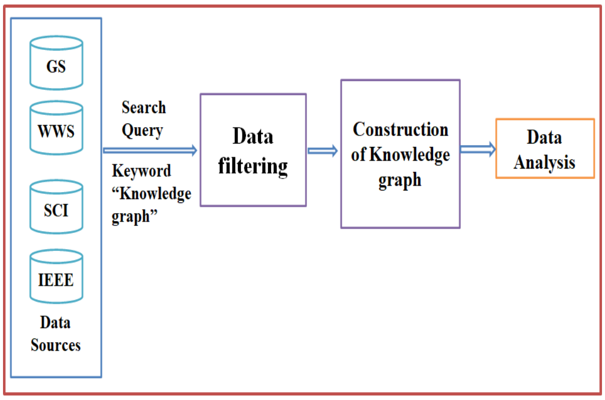


Fig. 3: Knowledge graph keyword search analysis proposed Methodology

4.1 Data source

The four prestigious research repositories Google Scholar (GS), IEEE Xplore, Science, and Worldwide Science (WWS) shown in Table 3 are taken as the data source for this study. The search criteria (e.g., Keyword "Knowledge Graph") are posted on each of the repositories.

Table 3: Sources selected for review.

Source	URL	Type
Google Scholar	https://scholar.google.com/	Free
Worldwide Science	https://worldwidescience.org/	Free
Science	https://www.science.gov/	Free
IEEE Xplore	https://ieeexplore.ieee.org/Xplore/home.jsp	Free and paid (both)

4.2 Data Filtering

In this methodology, the search query (e.g., keyword) will be considered as the set of rules or input and the data repositories are the source of data. The search query is run on one of the selected repositories that are mentioned in the data source part. The result of the search query is filtered based on two criteria: the first criterion is to select papers published during a specific duration (2000-2022), after applying the first criteria the result of the search query is collected but this is unfiltered data, on this data advance filtered is applied which will give a more accurate result.

In the advanced filter, the second criteria of the search query are applied that is – the search keyword should be present in the title of the document. This helps in getting specific research articles. For example, if the search query is "Keyword-knowledge graph", the filtration step is applied to it that is the research article should be published during 2000-2022 and the repository will return only those research articles for the query that have the search keyword in their "title". This will eliminate unnecessary data from the search results. In this study for experimentation purposes, the four keywords considered are Knowledge graph (KG), Knowledge graph embedding (KG Embed) [68)], Recommendation system knowledge graph (RS KG), and Recommendation system in the education domain (RS in education). These research areas are latest topics in research fields, as the time is forwarding towards recommending things the usage of knowledge graphs has also increased. Due to this hype this research includes keywords like knowledge graph it will shows the studies that include the knowledge graph and how it is used. The first keyword is related to what the topic is and the next three keywords are related to how the knowledge graphs are used for performing the research work. The next keyword is Knowledge graph embedding in this the nodes and edges are represented in vector form that helps in understanding the things nodes and edges are representing. The third and fourth keywords shows the domain in which the knowledge graphs are used which helps in finding the usage of knowledge graphs in specific domain. These are some topics for research which can be expanded in future work which will include other domains and topics for more specific research.

4.3 Construction of knowledge graph

The result of the data filtering part will act as input for this step. For the construction of a knowledge graph, a dataset is required. The dataset used for this experimentation is created from the results collected from the second step. The dataset contains two columns one is the year, and the second is the total number of papers published in that specific year. By using this dataset, the graphs and knowledge graphs are created for this experimentation.

4.4 Data Analysis

For data analysis, the input will be the Graphs and knowledge graphs that are created in the third step. The dataset is visualized in the form of graphs, these graphs help analyze the data are and also helpful in predicting future trends from the information. The graphs with specified years aid in the discovery of trends in the field of knowledge graph research. This also allows researchers to see whether repositories have a lot of data on specific keywords. All of the repositories, as well as the countries that contribute to this study topic, are represented in the knowledge graph this will help them in finding the right data in the right place. The data analysis helped in learn about the trends, strategies, and methodologies in the knowledge graph field that are of high research interest.

5. Experimentation and Result Analysis

This section contains information about the dataset as well as a discussion of the results obtained from keyword searching. The dataset used for the experimentation is prepared by combining data from the data source specified in section 3. In Table 2 and Table 4, an example of the dataset format is shown. Table one shows the data for the keyword "Knowledge graph" where there are two attributes: one is a year and the second is the repositories used for collecting this data for the year range 2000-2022. This information is the same for all four keywords that are used in this experiment.

But for the creation of a knowledge graph and a simple graph for the comparison of four repositories the dataset used is shown in table 5.

Table 4: Dataset used for creating the graphs of knowledge graph keyword.

Keyword / Repositories name	Knowledge Graph (KG)	Knowledge graph embedding (KG embedding)	Recommendation system Knowledge graph (RS KG)	Recommendation System in Education (RS in Education)
Google Scholar	5200	551	40	26
IEEE Xplore	1148	110	14	13
World Wide Science	2562	300	53	69
Science	587	4	3	12

Table 5: The dataset used for creating a comparison graph and knowledge graph.

Year	Total number of papers published in Google Scholar (KG)	Total number of papers published in IEEE Xplore (KG)	Total number of papers published in World Wide Science (KG)	Total number of papers published in Science (KG)
2000	1	0	0	1
2001	2	0	0	0
……				
2019	810	149	102	7
2020	1000	285	164	4
2021	980	408	276	13

The four keywords that are used for this experimentation are *Knowledge graph (KG), Knowledge graph embedding (KG Embed), Recommendation system knowledge graph (RS KG),* and *Recommendation system in education domain (RS in education)* used as the search criteria. The usage of these keywords shows the influence of knowledge graphs in the research field and how fast it's growing influence in other applications like recommendation systems and other domains like medicine and education but in this research, the focus is on the education domain.

K=Keywords, S=search repositories, C=count number of papers, P= Number of papers.

For this research, the preprocessing is done by using the algorithm proposed below:

Algorithm

1. *SELECT K in S.*
2. *Select Keywords used for web scraping in the four repositories.*
3. *Fetch C in S*
4. *Use web scraping to get the C in P.*
5. *Data collected is raw data, performed data mining on the data, and saved the data in data frames for easy use.*
6. *After collecting the data convert the data into a CSV dataset file.*
   i) *The dataset is then used for visualization.*
   ii) *Two methods used for visualization: first by Bar graphs, and second by knowledge graphs for finding the trending topic in the knowledge graph research field.*
7. *The knowledge graph from the dataset is created using neo4j to show the relationship.*

The results that are achieved by performing the method are discussed below:

5.1 Result in analysis for the keyword "Knowledge Graph"

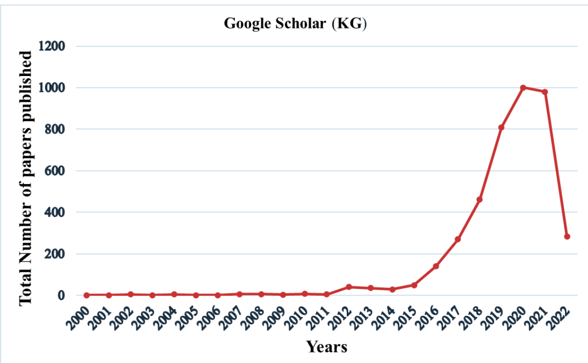
This section depicts the results obtained from the search query "knowledge graph" for the number of papers, journals, books, abstracts, and transactions published in these four research repositories, with the year range 2000-2022 according to the search criterion. Further, the search result is restricted by filtering as stated in the data filtering framework explained in section 3. to reduce the search space to the document's title and that the year range is 2000-2022. After the filtration process, the results are very accurate and there are only those articles that are specifically related to the keyword as shown in Fig. 4. Figure 4 shows the papers published in the four repositories with filtration and without filtration. Without applying the filtration, it is quite visible that the total number of papers getting for the search query is enormous in amount as compared to the result that is achieved after the filter is applied.

Figure 4.a. and Figure 4.b. show the total number of papers published in specific years in Google Scholar. Fig. 4.a. displays the total number of papers in Google Scholar, which is 1000. In Google Scholar one query can only return 1000 results, so for the KG query, the result shows the top 1000 research papers that are closely linked to the queried Fig. 4. c, Fig. 4. e, and Fig. 4. g shows the papers published in specific years in IEEE Xplore, World Wide science and Science.gov respectively, but this result is achieved by applying the filter. Fig. 4. c. displays a total of 1148 papers that were submitted. Figure 4.g. depicts the science.gov database, which contains a total of 524 papers connected to the knowledge graph, including both text and public access files. Papers, abstracts, articles, theses, reports, and

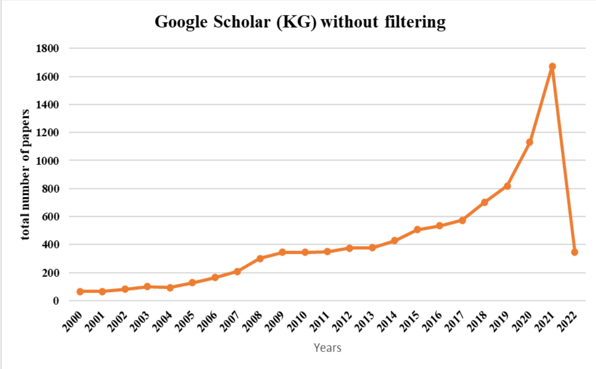
books are all included in text files. the total number of publications in World Wide Science (WWS) is 2309.

Similarly, Figure 4.d, Figure 4. F, and Figure 4. h show the papers published in specific years in IEEE Xplore, World Wide Science, and Science.gov respectively, but this result is without the filter. After visualizing the papers for specific years, the study visualizes the data of the total number of papers published in the years 2000-2022 in all four repositories. Figure 4. i and Figure 4. j show the comparison of the total papers published in all four repositories for the year range 2000-2022. As it is clearly stated the unfiltered data is very immense as compared to the data with a filter. From the graphs in Fig. 4, the following things can be analyzed:

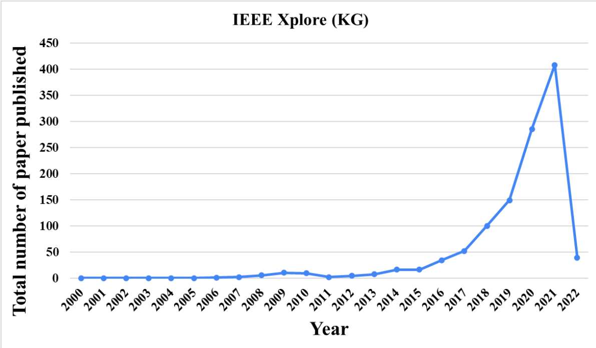
- The unfiltered data is immense as compared to the filtered data and the filtered data is specific and more relevant to the keyword used in the search query.
- From the four research repositories Google Scholar has more data and Science.gov has less data for the research keyword “knowledge graph”.
- From the last Fig. 4. i and 4. j, the leading repository in terms of data visible is Google Scholar, and the margin between unfiltered and filtered data is immense.
- The research on this topic has risen since 2013, as seen by the rising slope in 2013. This surge in this research topic is due to the impact of Google's decision. Google on May 16, 2012, announced that they are using a knowledge graph in their search engine to enhance the search results. They are using a knowledge base for this and they termed it Google's Knowledge Graph. After this announcement, the knowledge graph becomes a hot topic for research. The increase in the research of knowledge graphs is due to this decision.
- In the year 2022 the graph bar is low, that's because the study was done in April 2022 so not many papers are published at this time but from the previous graph bars, the prediction is that the research on KG will increase.



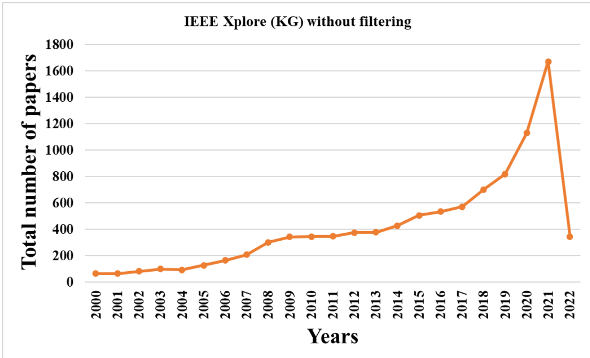
a. The total number of papers published in Google Scholar with filtration



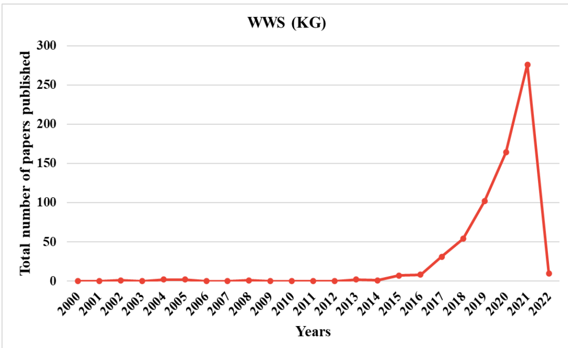
b. The total number of papers published in Google Scholar without filtration



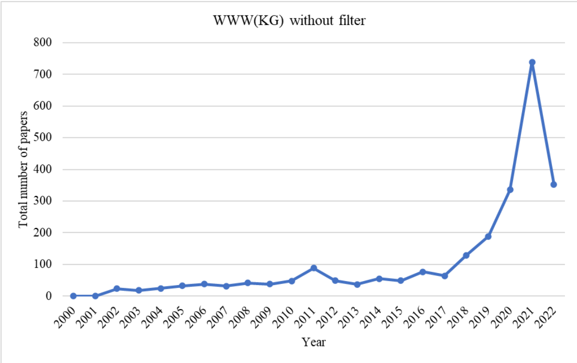
c. The total number of papers published in IEEE Xplore with filtration



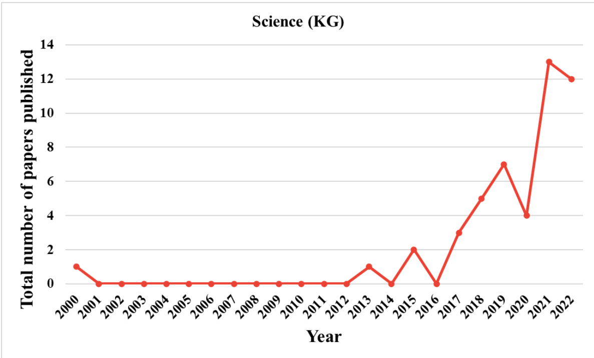
d. The total number of papers published in IEEE Xplore without filtration



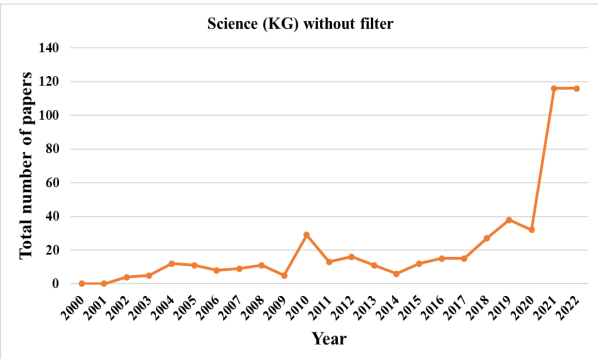
e. The total number of papers published in WWS with filtration



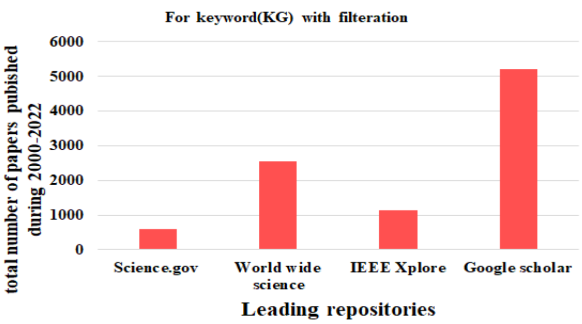
f. the total number of papers published WWS without filtration



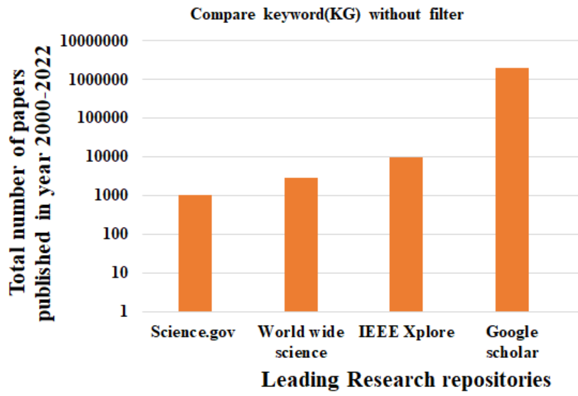
g. the total number of papers published in Science with filtration



h. the total number of papers published in science without filtration



i. The total number of papers published in all repositories for the keyword “KG” with filtration



j. The total number of papers published in all repositories for the keyword “KG” without filtration

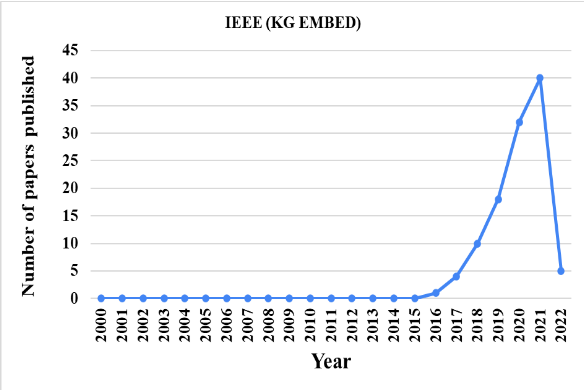
Fig. 4. Total number of papers published from 2000-2022(keyword KG)

5.2 Top subject field contributing to research on knowledge graph

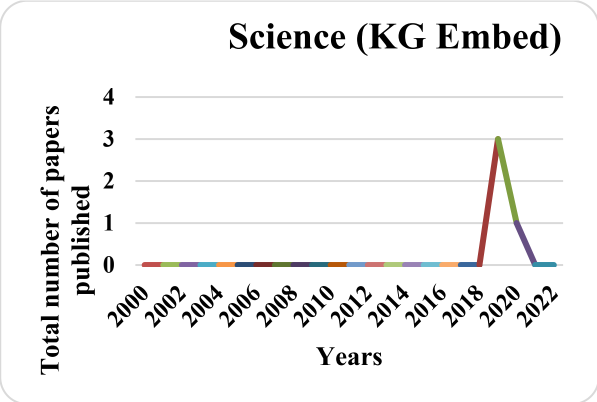
The search result of the keyword “knowledge graph” provides additional information that contributes to the rapid increase in the research of knowledge graphs like machine learning, entity extraction, knowledge graph embedding, domain-specific knowledge graphs, and the use of knowledge graphs in applications (like recommendation systems). The articles of the World Wide Web and IEEE Xplore concerning knowledge graphs are generally distributed into different subjects that contribute to knowledge graph research. Hence, the experimentation part is extended for the search of hype subjects in the knowledge graph. For this experimentation, the keywords included are “Knowledge graph embedding (KG embedding), recommendation system knowledge graph (recommendation system KG), and recommendation system in education”. The result of these is discussed below:

5.2.1 Keyword “Embedding in Knowledge Graph”

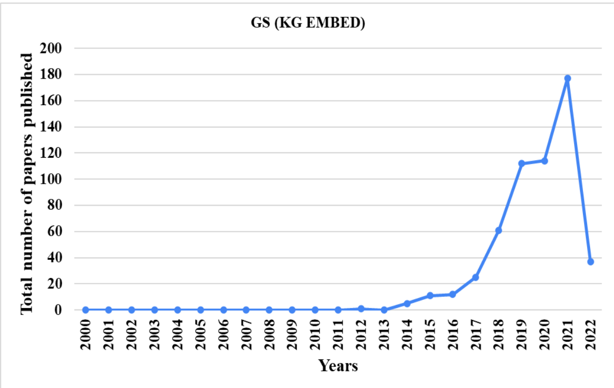
This section illustrates the number of articles retrieved for the keyword Embedding in the Knowledge graph as a subpart of the knowledge graph search. Figure 5 shows the results of the search that is done by using the KG embedding keyword in four repositories. Figure 5. a, Figure 5. b, Figure 5. C and Figure 5.d represent the total number of papers published during 2000-2022 in IEEE Xplore, Science.gov, Google Scholar, and World Wide Science respectively. For this keyword, the data is more in Google Scholar as compared to other repositories.



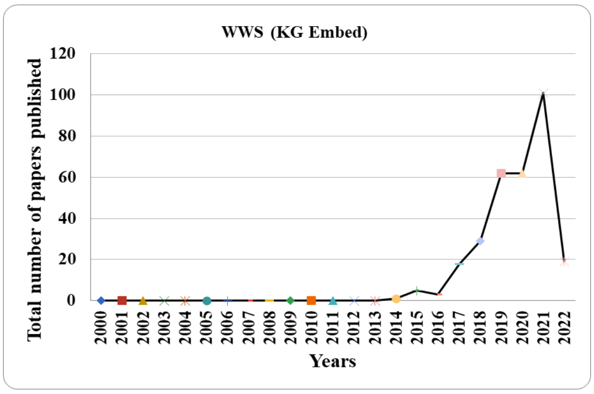
a. In IEEE Xplore



b. In science.gov



c. In Google Scholar

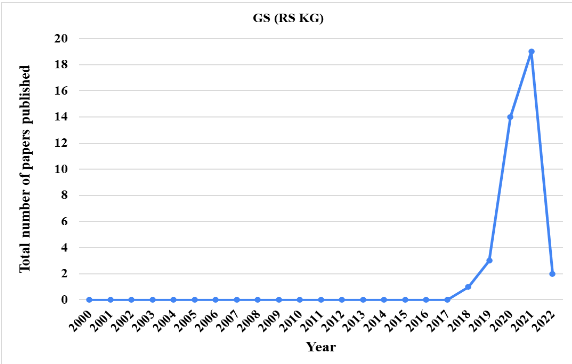


d. In Worldwide science

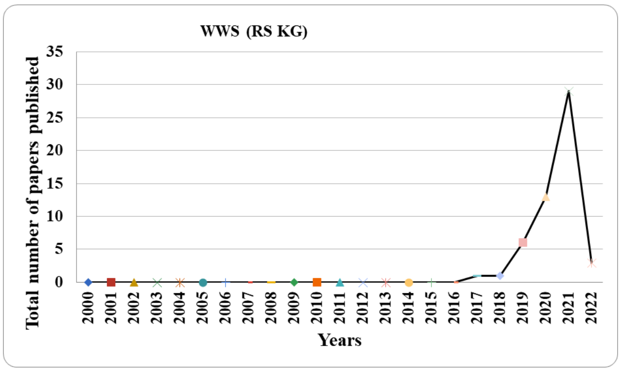
Fig. 5: Total number of papers published in 2000-2022(search keyword used KG embedding)

5.2.2 Keyword "Recommendation system in knowledge graph"

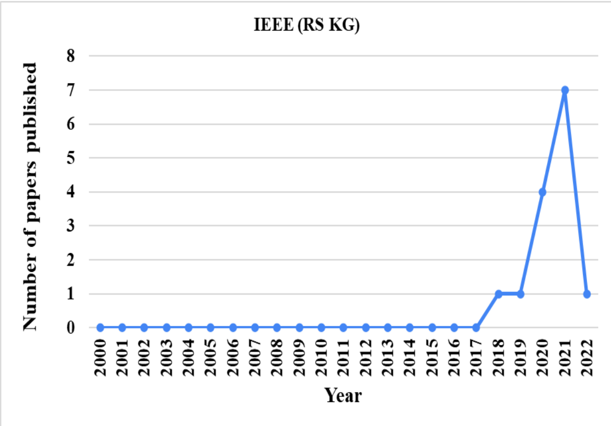
After the literature survey, anything that is more popular than embedding methods in a knowledge graph is a recommendation system. Recommendation systems are very much in demand in the research area as anything we see has a recommendation system, whether online platforms for movies, shopping, or any article. If we read or see something, the system will recommend to us another thing of the same genre as we see movies then automatically the apps suggest we watch another movie of the same genre. The next keyword for experimentation is "Recommendation system in knowledge graph". Figure 6 shows the total work done on the recommendation system in the knowledge graph domain, Figure shows the data that is present in all four repositories. Figure 6. a, Figure 6. b, Figure 6. c and Figure 6.d show the no of papers published throughout 2000-2022 in Google Scholar, World Wide Science, IEEE Xplore, and Science.gov respectively. It is visible from the graph that WWS has more papers as compared to other repositories.



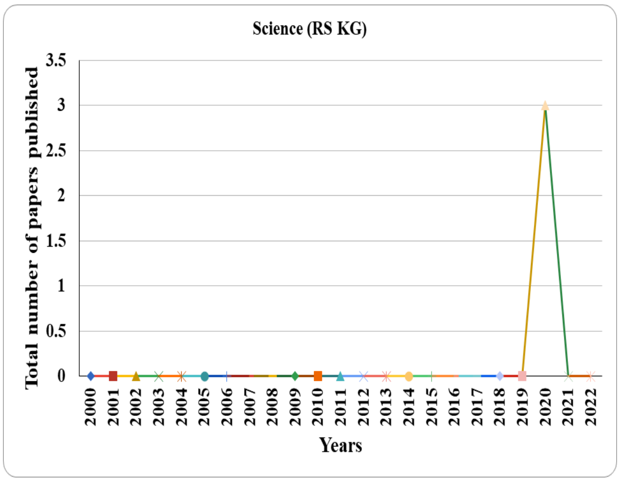
a. Papers in Google Scholar



b. Papers in WWS



c. Papers in IEEE

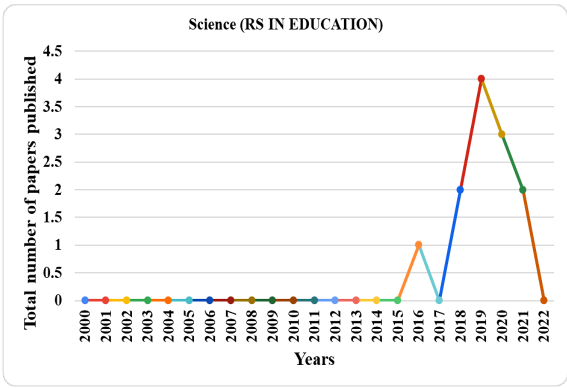


d. papers in Science.gov

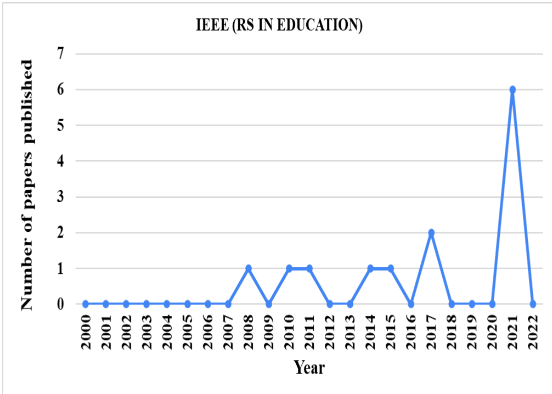
Fig. 6: Total number of papers published for the keyword Recommendation system knowledge graph

5.2.3 Keyword "Use of recommendation system in education"

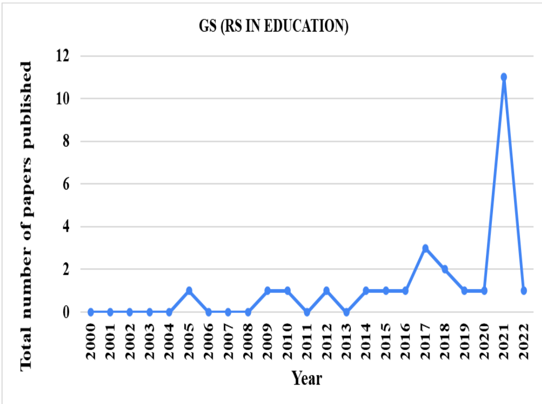
The scope of the recommendation system in the knowledge graph is in demand. Domain-specific knowledge graphs are also an emerging topic for research. However, this research paper cannot include all the domains so this research is limited to only one domain which is education. During the pandemic, the most hit domain is education, as the education system has to move to the online platform. So, the search includes the keyword "recommendation system using knowledge graph in education" but the result shows no papers related to the keyword as the search criteria have filtered applied to the document title in the advanced search option of the research repositories. To get the results the keyword is a little modified with other words like "recommendation system in education". So, the results achieved can be seen in Fig. 7. Figure 7 shows the total number of papers published in the year 2000-2022. Figure 7. a, Figure 7. b, Figure 7. C, and Figure 7.d show the total number of papers published in science.gov, IEEE Xplore, Google Scholar, and World Wide Science respectively. From Fig. 7 it is visible that WWS has more papers as compared to other repositories.



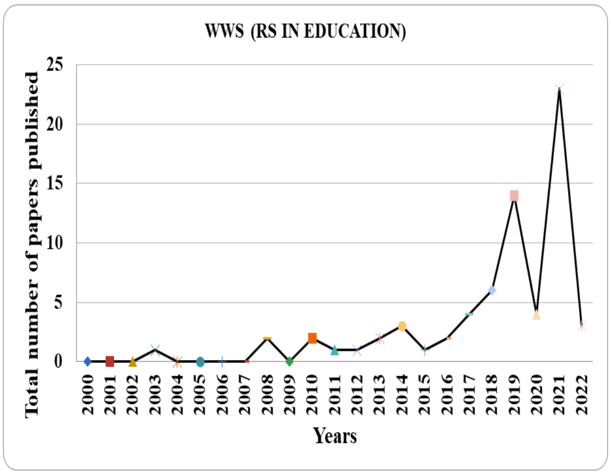
a. papers published in Science



b. papers published in IEEE Xplore



c. Papers published in Google Scholar



d. papers published in WWS

Fig. 7: The total number of papers published in 2000-2022 for keyword recommendation systems in education.

5.3 Comparison of all the four research repositories

This section combines the search results of all four keywords from the four repositories of individual years as year range like 2000- 2022. Figure 8 illustrates the comparison of all the repositories based on four keywords that are used for performing the experimentation. Examining Figure 8 indicates that Google Scholar has more papers on the knowledge graph as compared to other research repositories but for the keyword, KG embedding the IEEE Xplore has more data. Papers on the third and fourth keywords are fewer as is visible on the graph. Scinece.gov has fewer papers as compared to the other three research repositories. The relationship of these repositories with the keywords is represented by creating a knowledge graph as shown in Fig. 9. In this knowledge graph, the nodes represent the four repositories (Google Scholar, IEEE Xplore, World Wide Science, Science) and the total number of papers published for each keyword. The nodes of numbers are connected with the nodes of research repertories with the relationship edge. The knowledge graph gives the relationship of keywords with the repositories, and which repository has immense data is shown by the knowledge graph constructed. It is shown in the knowledge graph how nodes are connected; the graph is connected to the nodes very well.

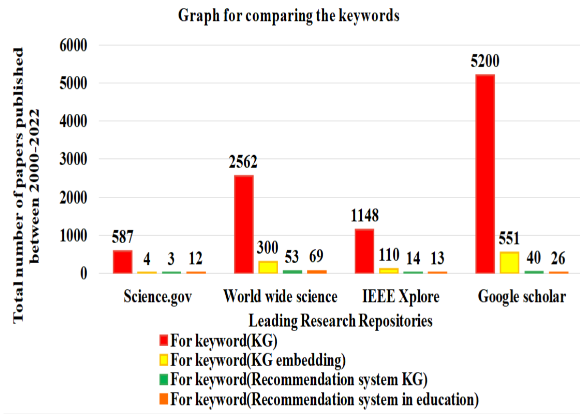


Fig. 8: Comparison of repositories based on the search keywords

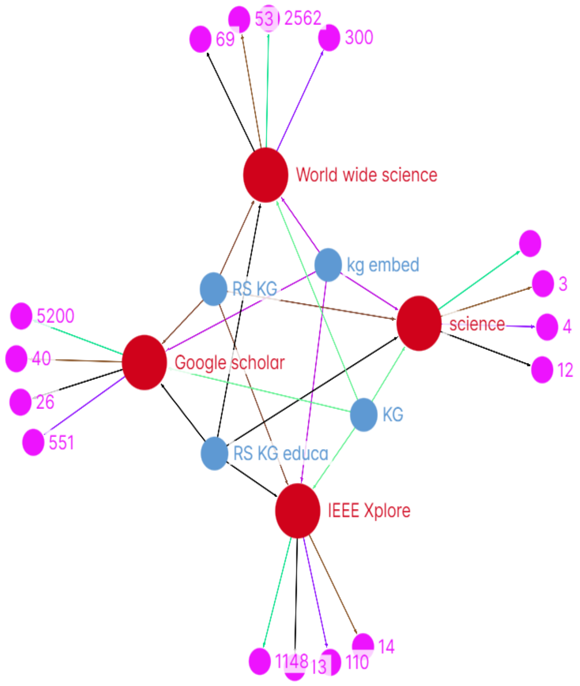


Fig. 9: Knowledge graph of all the repositories with the total number of papers

5.4 Top countries contributing to the research

The articles and papers concerning knowledge graphs and other search keywords are contributed by many countries and regions. When the search query is run for the keyword in the WWS repository the result also shows which country is contributing and how many papers. This shows which country is at the top in research in the knowledge graph. In Table 6 the top 16 countries that are contributing to the research are shown. From Fig. 10, it is quite clear that the United States is at the top with 893 total papers and Italy is last with 7 papers. This data is collected from a worldwide science research repository. In Fig. 11, the nodes connected with the country nodes show the inter-reliability of the research field and its papers of the countries and their contribution to this research field.

Table 6: Total number of papers contributed by the following countries on every keyword search

Countries	KG	KG embedding	RS KG	RS in education	Total
United States	533	136	119	105	893
Canada	200	157	162	136	655
Czech Republic	128	100	100	102	430
Ireland	110	112	200	0	422
Finland	100	5	43	58	206
India	100	100	100	50	350
Japan	100	54	89	90	333
Netherlands	100	20	4	50	174
Korea	99	5	2	64	170
China	90	80	70	20	260
Germany	53	50	51	49	203
Saudi Arabia	50	50	50	50	200
United Kingdom	50	50	50	10	160
Russia	16	29	110	62	215
Norway	15	2	0	15	32
Italy	7	0	0	0	7
Estonia	0	50	50	50	150

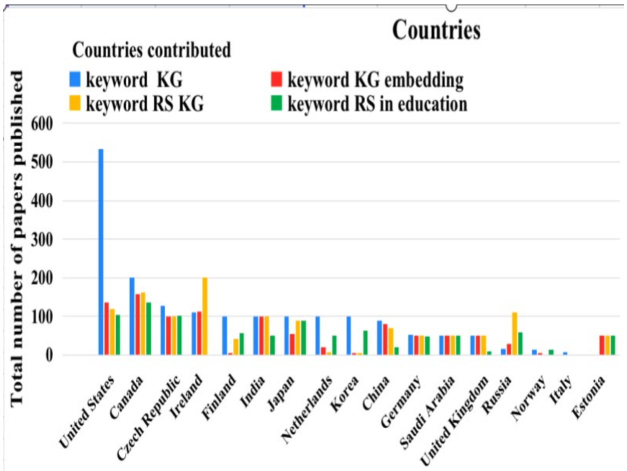


Fig. 10: Articles and papers concerning knowledge graphs and other searching keywords Contributed by countries

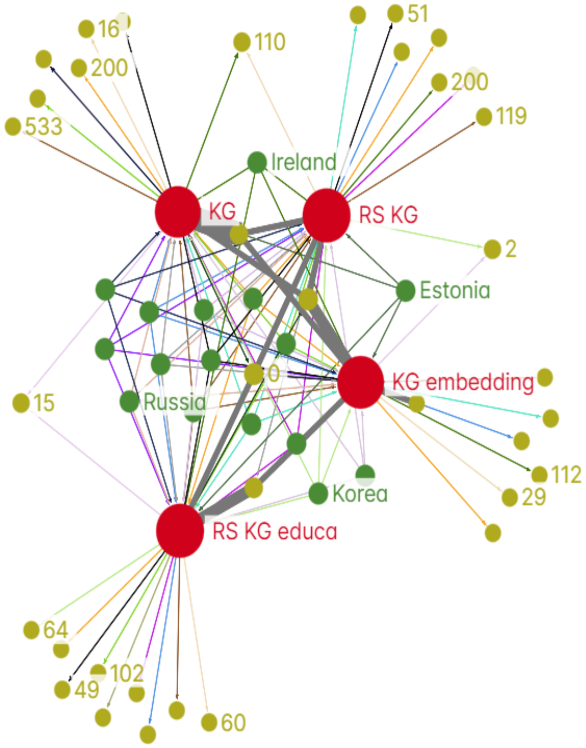


Fig.11: Knowledge graph of countries connected with the keyword search result

6. Conclusion

This paper is based on the topic analysis method; which collects information about different papers, theses, and articles on knowledge graphs. The result of the experimentation helps researchers in getting the hot topic in the research field. The paper is trying to give an overview of the knowledge graph, helping enthusiastic students in selecting the trending field for research in knowledge graph domain and also it helps in deciding the students to contribute in the topic and how students can contribute to creating novelty by doing new research in the fields of the knowledge graph, and also an overview of the recommendation system. By the use of graphs and knowledge graphs we can see the trending topic for research. This helps in extracting the knowledge of different topics in the subject of research in knowledge graph. The experimentation study includes four research repositories that are Google Scholar (GS), IEEE Xplore, Science, and Worldwide Science (WWS). From these four repositories, the research includes research papers, articles, books, and a thesis on the topic of Knowledge Graph (KG). The experimentation is based on web scraping the data from these repositories and creating a dataset from the raw data by preprocessing it using data mining techniques. The data is fetched based on keyword searching, and for this experimentation, there are four keywords used, that are Knowledge graph (KG), Knowledge graph embedding (KG Embed), Recommendation system knowledge graph (RS KG), and Recommendation system in the education domain (RS in education). By using these four keywords the data on the number of papers, articles, and books that are present in these four repositories from 2000 to 2022 is collected. After this visualization of the data by using graphs and knowledge graphs is done which gives the result that Google Scholar contains more data as compared to other repositories. The result shows that the knowledge extracted from the above queries helps in finding the results through visualization which helps the researchers to do research on topics which has less data. One more thing is that after 2012 an increase in the research in the knowledge graph domain is seen. This shows that if research students want to dig into the research on this topic, then they can get the maximum information and research work in the Google Scholar repository. This study also shows which country is contributing more to the knowledge graph domain.

In future work, different methods will be used for creating the knowledge graph, and also for the keyword searching only four different keywords are considered but in future work, this will consider other aspects such as the author network and the organization network. Metrics will also be used to evaluate the efficiency of this model and the algorithm proposed. Future studies will contain more comprehensive analyses that will help in more research development.

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