The Power and Potentials of Flexible Query Answering Systems

A Critical and Comprehensive Analysis

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Publication date:
2022

Document Version
Other version

Citation for published version (APA):
Andreasen, T., Bordogna, G., De Tré, G., Kacprzyk, J., Larsen, H. L., & Zadrozny, S. (2022). *The Power and Potentials of Flexible Query Answering Systems: A Critical and Comprehensive Analysis*. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4292638

Graphical Abstract

The power and potentials of Flexible Query Answering Systems: a critical and comprehensive analysis

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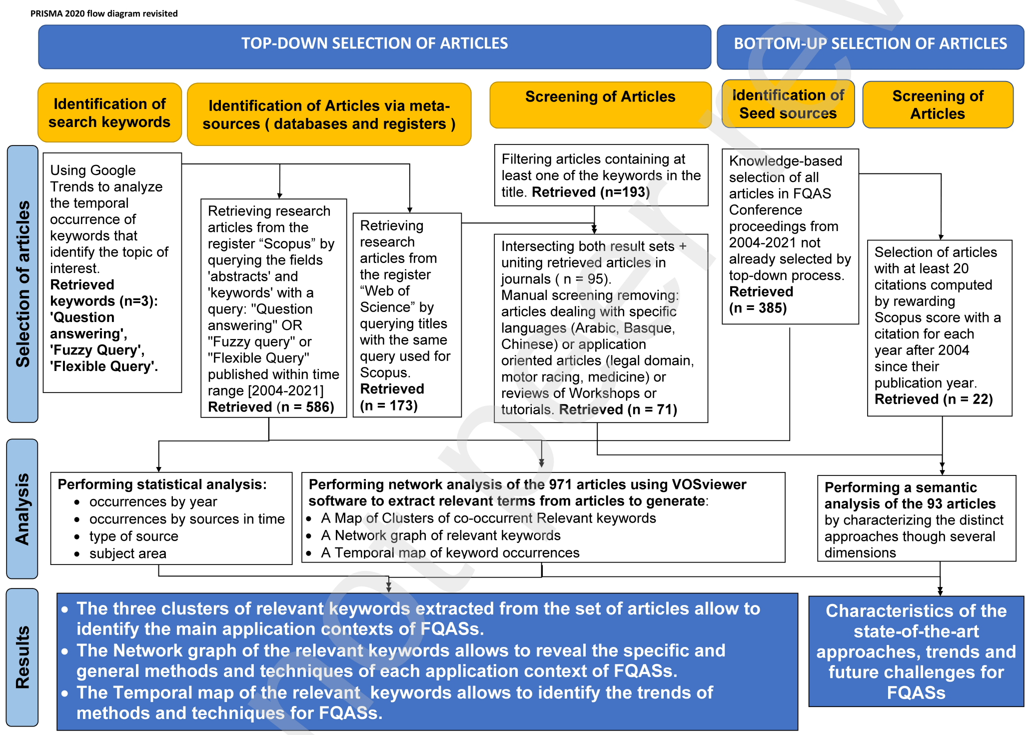

Highlights

The power and potentials of Flexible Query Answering Systems: a critical and comprehensive analysis

Troels Andreasen, Gloria Bordogna, Guy De Tré, Janusz Kacprzyk, Henrik Legind Larsen, Sławomir Zadrożny

- Top-down and Bottom-up analysis of research literature on Flexible Query Answering Systems;
- Semantics classification of approaches;
- Identification of recent trends and future challenges;

The power and potentials of Flexible Query Answering Systems: a critical and comprehensive analysis

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Abstract

The paper presents a critical and comprehensive analysis of recent developments, trends and challenges of Flexible Query Answering Systems (FQASs). Flexible query answering is a multidisciplinary research field at the crossroad of several disciplines among which Information Retrieval (IR), databases, knowledge based systems, Natural Language Processing (NLP) and the semantic web, which aims to provide powerful means and techniques for better reflecting human preferences and intentions to retrieve relevant information. The analysis follows the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines characterized by a top-down process, starting with relevant keywords for the topic of interest to retrieve relevant articles from meta-sources, and complementing them with relevant articles from seed sources identified by a bottom-up process. To mine the retrieved publication data a network analysis is performed which allows to present in a synthetic way intrinsic topics of publications by revealing aspects of interest. Issues dealt with are related to both query answering methods, both model-based and data-driven, the latter based on Machine Learning, and to their needs for explainability and fairness, and big data, notably by taking into account data veracity. Conclusions point out trends and chal-

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Preprint submitted to Information Sciences *November 21, 2022*

lenges to help better shaping the future of the FQAS field.

Keywords: flexible query answering, model-based query answering, data-driven query answering
PACS: 0000, 1111
2000 MSC: 0000, 1111

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1. Introduction

Since the seminal paper by Turing [127] that proposed the well-known Turing test, the assessment of the level of intelligence of a machine, that is an algorithm, automatic agent or system, is performed by evaluating the ability of the machine to simulate human conversation. Even if nowadays the Turing test is questioned as a real indicator of intelligence, it has to be admitted that to pass such a test a machine should master many abilities of human beings, including not only natural language understanding and generation, but also knowledge representation and reasoning, learning, interpretation of human emotions and multimodal information in the form of human gestures and facial expressions, to name just a few. Among such abilities, an important role has been attributed to the ability to answer queries despite their imprecise and/or incomplete wording, taking into account the context in which they are formulated, exploiting common sense knowledge, etc. Thus, to pass the Turing test, a machine has to be equipped with the methods researched in the broad field of Flexible Query Answering Systems (FQASs).

FQASs have the distinguished characteristics to help formulate and then evaluate queries so as to better satisfy the needs and search intentions of the users. This is achieved by taking into account specific aspects of human communication when searching for information. Although an issue of FQAS is finding the right or best answer in small data collections, both structured and unstructured, naturally, the real focus in the field of FQAS is the so-called big data, i.e., data that cause problems on volume, variety, velocity, veracity, etc. when handled by conventional systems.

It is apparent that flexible query answering is strongly related to the field of human-computer interaction (HCI) defined by the Association for Computing Machinery (ACM) as "...a discipline that is concerned with the design, evaluation and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them" [61]. This concerns both technical issues related to storage, management and visualisation of data, just to mention a few, and modeling issues related to human communication, argumentation, explainability, natural language understanding and generation, cognitive and psychological analysis, among others. More recently, with the widespread availability of user-generated contents and big data, flexible querying is invariably affected by the data veracity issues. As such, data are often affected by uncertainty, imprecision, vagueness, incompleteness, etc. which should be adequately modelled. Moreover, data veracity issues in FQASs are often imposed by the use of multiple data sources, which cannot all be trusted to the same extent.

In this paper, as depicted in Figure 1, in order to present a comprehensive, critical and constructive account of main approaches and future challenges of FQASs, we perform a critical, systematic literature review and analysis of the diverse conceptual and implementational approaches to FQASs. Herewith, we adopt the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines [102] which are widely advocated. Firstly, we will follow a top-down process by selecting and reviewing articles from the Scopus and Web of Science registers based on relevant keywords. Furthermore, we will complement the top-down review with a bottom-up process, starting with seed sources that we know contain relevant articles on the topic of interest, that might be missed by the top down selection [36]. Finally, a classification of the approaches proposed in the selected articles is carried out based on several semantic characteristics such as (i) the kind of information dealt with, (ii) the type of interaction, (iii) the search intent and the type of answers, (iv) the retrieval model, (v) the type of system and its implementation requirements and constraints. This multifaceted and comprehensive analysis will serve to identify the main methods, discover and trace some emerging, novel and promising approaches and directions of research in the field, notably in view of the rapid development of the broadly perceived AI and data sciences.

This paper is organized into five sections. Section 2 describes the method applied for the selection of the relevant literature. Section 3 describes the network and semantic analysis of the relevant literature. Section 4 describes the challenges of the research on FQASs. This is followed by conclusion and future direction in Section 5.

2. A Critical and Comprehensive Literature Review Selection

The flow diagram compliant with PRISMA guidelines that we applied for the top-down and bottom-up selection and analysis of the FQAS literature is depicted in Figure 1. From top to bottom, first the relevant literature is identified, next analysed and finally results are discussed. The left hand-side of the flow diagram depicts the steps of the top-down analysis for the identification of the relevant literature, in which first representative keywords that describe the topic of interest are selected. Next, the meta-sources, that is the registers and databases, where to search for the selected keywords to retrieve the relevant literature to analyse are identified.

The right hand-side of the flow diagram depicts the steps of the bottom-up analysis, based on the knowledge of seeds sources of relevant articles on the topics of interest: we considered that all FQAS conference proceedings articles are pertinent to the topic of flexible query answering systems, even if they are not retrieved by the top-down search.

On the union of the articles retrieved by both the top-down and the bottom-up analysis a network and temporal analysis was performed.

Results comprehend both the contexts of application of the topic of interest identified by the most relevant keywords extracted from the articles' titles and abstracts, characteristic methods for each context, and temporal trends of the methods.

Finally, for selecting a meaningful and manageable set of scientific articles a further screening was applied on which a more refined semantic analysis was performed.

Results comprehend a characterization of the diverse approaches proposed in the selected articles according to several semantic dimensions which allow to identify both the major and minor approaches proposed together with their specific aspects.

2.1. Identification of Article's Meta-sources and Search Keywords

To identify the most relevant research articles we decided to select as relevant meta-sources the electronic repositories of Scopus and Web of Science (WoS) and to perform searches by submitting a set of queries.

To decide which keywords to use for searching publications, we first performed an exploratory analysis of the most common terms, relevant for the topic, by using Google's Trends tool.

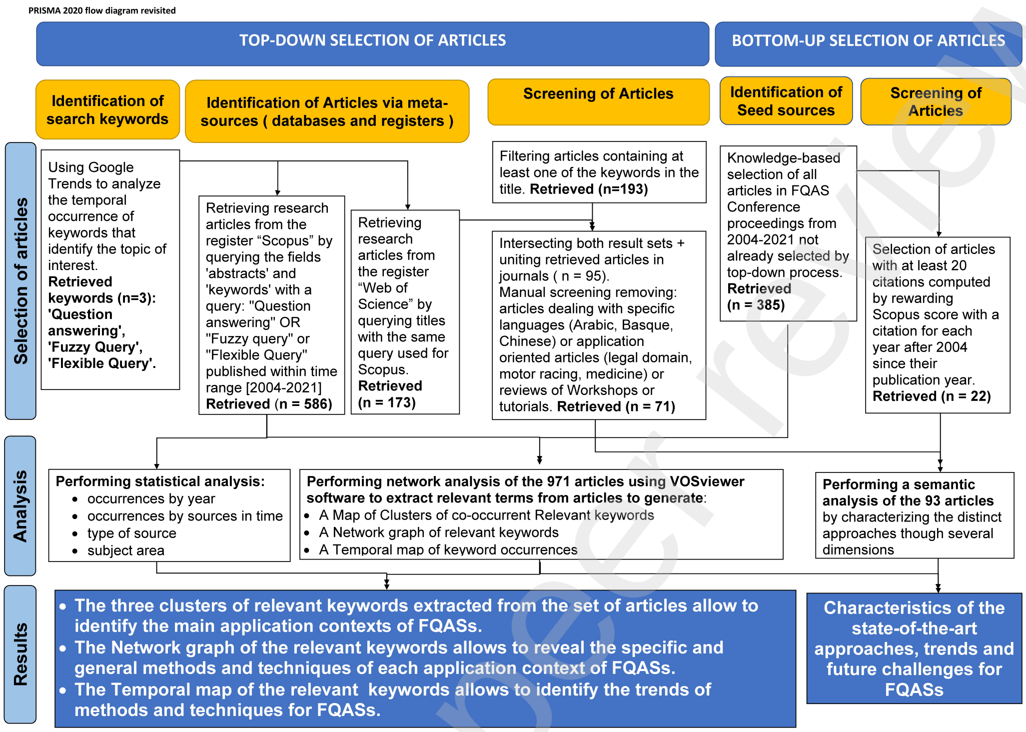

Figure 1: Flow diagram of the top-down (left) and bottom-up (right) procedures applied for the identification, screening and analysis of the relevant literature compliant with PRISMA guidelines.

Among the keywords we explored as possible representatives of the topic of interest, the six most popular ones are the following:

sentiment analysis, *elastic search*, *query language*,
question answering, *fuzzy query* and *flexible query*.

We decided to discard *elastic search*, since it is mostly related to the Elasticsearch engine, as it is strictly associated with the keywords *API, Kibana*, and thus the correspondent searches are not specific to FQASs. Moreover, we also discarded *Sentiment analysis* and *query language*, being both too general keywords, involving topics more general than FQASs.

2.2. Identification of Articles by the Top-Down and Bottom-up Analysis

Based on the analysis of the relevant keywords, we submitted a query to Scopus by considering a time span from 2004 to the end of 2021 and limiting the search to specialised journals and conferences.

Scopus returned 590 articles by searching keywords within titles, abstracts and keywords. We removed articles which were evidently not on the topic (four in total) and then retained the remaining 586 articles. Firstly, we observed that the number of published articles increases over time.

Secondly, we observed that the Springer's series LNCS, including its subseries LNAI and LN in Bioinformatics, are the most frequent source almost every year. The runner-up are the ACM Conference proceedings series, and, finally, the Journal of Intelligent & Fuzzy Systems and the International Journal of Intelligent Systems since 2005 and 2010, respectively.

As far as the types of sources of retrieved papers are concerned, the large majority (88.7%) are proceedings of conferences, then only 7.2% are journals, and the remaining are conference and journal reviews.

As far as the bottom-up analysis is concerned, as seed source we identified the FQAS conference proceedings from 2004 until 2021[131] and retrieved 391 articles by formulating a query to Scopus. Such articles are all relevant to the topic of interest, even if only 6 of them were retrieved also by the top-down process, the other not containing the search keywords in their title and abstract.

Finally, by removing the 6 duplicated articles we obtained a set of 971 articles in total, on which the network and temporal analysis was performed.

3. Analysis of the Selected Literature

3.1. Network and Temporal Analysis

We applied a network analysis by using the open software VOSviewer (downloaded from `https://www.vosviewer.com/`), a tool for network analysis based on clustering and text mining algorithms. In our context, we created maps of keywords extracted from the selected articles. Between each pair of keywords a weighted link (strength) is identified according to the co-occurrences of the keywords in the articles. The most relevant keywords, (i.e., most frequent and not in a stop-words list) were then grouped into clusters based on their links strength. Finally, we analysed the topics of the articles by exploring the three types of visualisation provided by VOSviewer: (i) the density map allows to visualise the relevant keywords and how they are clustered according to their co-occurrences in the articles; (ii) the network map allows to explore the most relevant linked keywords , (iii) the overlay map allows to analyse the temporal appearance of the keywords. The network map in Figure 2 displays the top 54 most relevant keywords with at least 10 occurrences, extracted from both the title and the abstract of the 971 articles that were obtained in the previous step, after applying stop-word removal.

These keywords have been clustered according to their relevance score and link strength: three clusters of keywords were identified, containing 16, 23 and 15 keywords in the red, green and blue clusters, respectively.

We can observe that the three clusters are roughly associated with the three main application contexts for "flexible query answering" and "question answering": (1) the core of the red cluster is related to "knowledge based systems", "Knowledge graphs" and "Natural Language processing systems", containing other relevant keywords such as "Knowledge representation", "natural language processing", "decision making", "Knowledge base" and "semantics"; (2) the core of the green cluster is relative to "community question answering" and "information retrieval" on textual documents, containing other relevant keywords such as "community based question answering", "question answering", "question answer pairs", "social networking", "factoid questions", "forecasting","information services", "information retrieval systems", and "search engines" ; (3) the core of the blue cluster is relative to "databases" and contains other relevant keywords such as "relational database", "data structures", "data warehouses", "electronic commerce", "flexible querying", "fuzzy queries", "intelligent systems", and "xml".

More in detail, if we consider the keywords that identify a method in the red cluster on "knowledge based systems" we can find "ontology", "semantic web", and "natural language processing"; in the green cluster on "community question answering" and IR we can find "classification of information", "deep learning", "learning to rank", "machine learning", and "neural networks"; the blue cluster on "databases" contains as keywords indicating methods "fuzzy logic", "fuzzy sets", "mathematical models", and "constraint theory".

Let us analyse the links of some relevant keywords in the network visualisation map. Although any keyword in Figure 2 has the greatest number of co-occurrences with other keywords belonging to its same cluster, our aim is to explore links between clusters, in order to identify possible shared methods and techniques in different clusters, i.e., application contexts.

We observed that the data-driven methods based on "neural networks" and "deep learning", appearing in the green cluster on "community question answering " and "information retrieval", mainly link to many keywords in the red cluster on "knowledge based systems", while there are only a few link to the blue cluster on "databases'; in particular, "learning to rank" is not

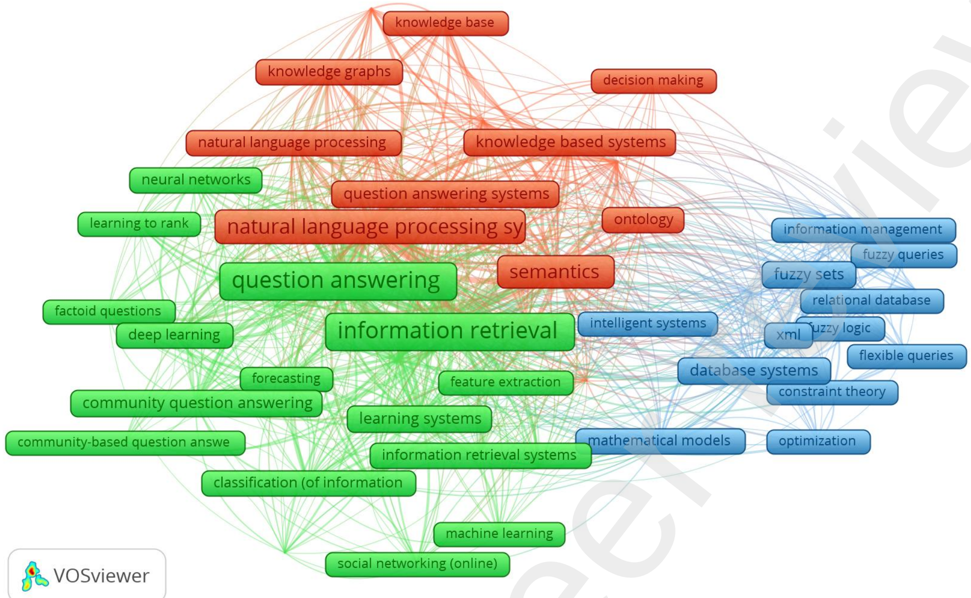

Figure 2: Network map of the most relevant keywords extracted from the 971 articles grouped into three clusters associated with the application contexts for "flexible query answering" and "question answering": the core of the red cluster is associated with "knowledge based systems" and "Natural language processing systems", the core of the green cluster is about "community question answering" and IR, and the core of the blue cluster is mainly about "databases".

linked to any keyword in the blue cluster, while "data mining", "ontology" and "semantic web" have many links to all clusters, meaning that these methods are relevant for all the three contexts.

Finally, we also observed that the keywords "Fuzzy logic" and "Fuzzy sets" appearing in the blue cluster on "databases" have only a few links to the red and green clusters, meaning that fuzzy approaches have been applied mainly in "databases". Concluding this part of the analysis, in the time overlay map in Figure 3 we can observe the most relevant keywords extracted from the selected articles with a specific colour representing the publication dates of the articles from which the keyword has been extracted. Among the keywords occurring in the relevant papers already at the beginning of this period we can find "database systems", "xml", "constraint theory" , "fuzzy queries" (in dark violet) while among the keywords occurring most recently we can find “neural networks” , “deep learning”and “knowledge graphs” (in yellow).

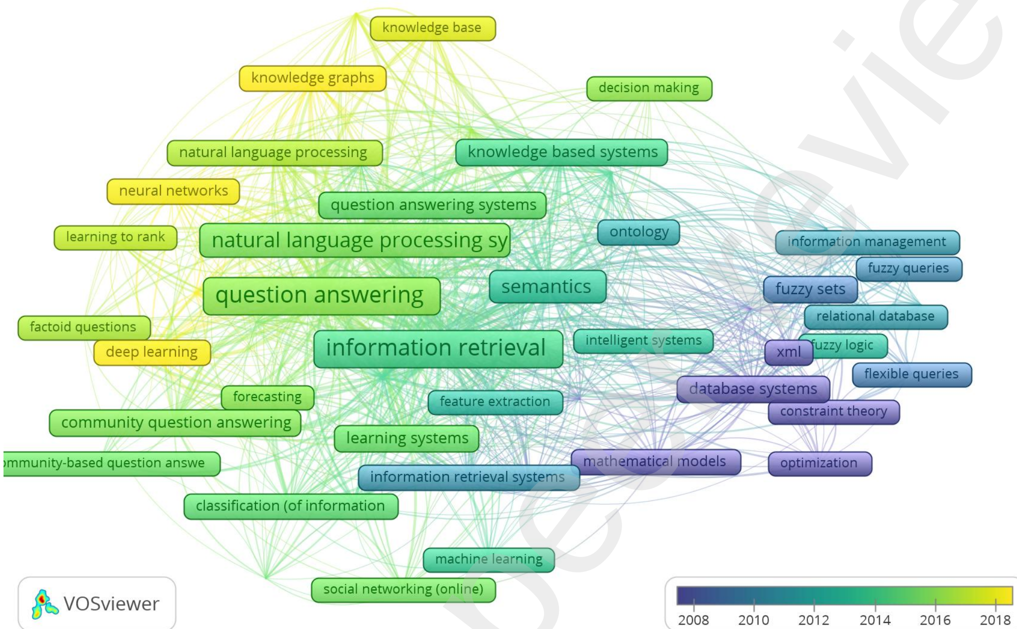

Figure 3: First occurrence in time of the most relevant keywords selected from the 971 articles according to their most frequent publication dates.

3.2. Semantic Analysis

The semantic analysis is applied to a subset of relevant articles filtered among the set of 971 publications previously retrieved by either the top-down or the bottom-up processes. As far as the 586 out of 971 articles retrieved by the bottom-up analysis, we filtered those published in journals or that were also retrieved by an equivalent query submitted to the WoS. Then, we manually eliminated publications that were about a specific language or domain, or were editorials or tutorials not proposing a specific approach, and thus not useful for the semantic analysis. We finally remained with 71 articles [78], [66], [85], [42], [136], [39], [115], [108], [2], [79], [152], [121], [37], [52], [122], [124], [33], [53], [132], [129], [117], [105], [11], [38], [109], [43], [123], [142], [97], [25], [55], [29], [148], [95], [149], [141], [30], [111], [4], [63], [126], [81], [70], [139], [135], [103], [94], [84], [71], [107], [134], [147], [128],

[67], [133], [80], [24], [138], [118], [86], [51], [58], [82], [31], [151], [72], [140], [49], [60], [28], [32].

This set was complemented with a subset of relevant articles filtered from those previously identified by the bottom-up analysis, consisting of the top 22 most cited publications appearing in the FQAS proceedings, with a weighted citation score above 20, computed proportional to the Scopus citation score by rewarding each year from its publication date after 2004 with a citation [114],[41],[119],[73],[8], [45],[106],[23],[137],[110],[65],[21],[26],[93],[9], [100],[17],[98],[16],[120],[112],[77].

The 93 considered articles are manually classified according to several main dimensions ("Kind of information", "Type of interaction", "Search intent/task" and "Type of answers", "Retrieval mechanism", "Type of system", and "Perceptiveness") the results of which are represented in the tree map in Figure 4.

3.3. Kind of Information

Most of the approaches deal with either structured data, in the form of knowledge bases and knowledge graphs, or collections of unstructured textual documents; other approaches deal with either structured data in tables , or semi-structured textual data, in the form of posts and XML documents; the minority deals with other kind of data, such as metadata, images, multimedia data, videos, sensor trajectories, music and implicitly structured tables, that is, web tables implicitly structured by a typography style.

Moreover, the majority of the approaches makes use of a benchmark collection, in the form of a Query or Question & Answer corpus, which, in more than half of the cases, is used for training the model by machine learning, while, in the other cases, it is directly used to select an answer in the context of community based question answering systems. These corpora are in either textual form, or structured form; sometimes are accompanied with images. Some data-driven approaches also employ profiles of either users or community or groups, user history, user and group ratings, and user click-through logs.

3.4. Type of Interaction

With respect to the type of interaction, a broad distinction is made between articles proposing a push or a pull technology: "pull" means that the user explicitly formulates a query in some way, i.e., natural language, a formal language like the Boolean language, SQL, SPARQL, a query-by-example, and using some templates; "push" means that the system automatically builds an implicit query, that is assumed to be expressing the users needs; implicit queries can be defined by exploiting, e.g., information from previous queries, metadata, contextual information, (fuzzy) rules. Both "push" and "pull" interactions imply an internal conceptual representation of the query that can be a (fuzzy) set, algebraic, graph or semantic representation. Most of the pull approaches accept queries in natural language, while the most common push approach uses metadata. Besides, some approaches apply both pull and push at the same time, e.g., by allowing both a query in natural language and an automatically built query by exploiting metadata. Considering the conceptual representation of either an explicit or implicit query, the three most represented ones are embedding, formal language expressions, and keywords.

3.5. Search Intent and Type of Answer

With respect to Search intent or task, "informational and factoid queries" are those most common, which ask for knowledge about something or someone like events, places, dates. Furthermore, in decreasing order of frequency we can find: "Contextual or topicality queries" that need to be answered by considering the context of the user, the session, and the collection; "Transactional queries" that involve mainly investigation of opinions, prices, recommendations; "Conversational and interactive searches", the evaluation of which is strongly dependent on the thread of previous queries; queries requesting some analysis, mining or discovery activity of implicit information, generally answered by summaries; "Predictive queries" asking for the best responder or expert on a given topic; "Non-factoid or procedural queries" which ask to respond to "how" something is done, which may require to retrieve a procedure, like a recipe that can be a video, or a sequence of images, or a text; "intent identification", which may need to disambiguate the query; finally,"List queries", that need the execution of some operation to select all items satisfying them, like in the query *List all European countries bordering the Mediterranean Sea.* Many approaches have more than a single search task, for example, they request answering factoid queries by either taking into account the context or disambiguation. Considering the answers, the most common type, which is typical for question answering systems, is either a single or a list of natural language answers. Then, follows the ranked list of either tuples, values or objects, like named entities, names of experts or best responders for the query. Some approaches evaluate a quality measure, like a trust score, for the retrieved answers or tuples. Other approaches yield clusters or classified groups of documents or answers; these last ones are generally retrieved from a question & answer corpus. Finally, we found approaches that yield a summary of either multiple documents or multiple snippets; documents' passages, or ranked lists of passages or snippets; a knowledge graph or a path on a triple; a classic ranked list of documents or posts; infographs (e.g., a word cloud or network representation); maps of Point Of Interest; tuples of a database; semantically enriched answers with links to some ontology or definitions of terms.

3.6. Retrieval Mechanism

First we distinguish between model-based approaches, which are the majority, and data-driven ones. Furthermore, we identified some hybrid models, which apply both model-based and data-driven methods.

Among the model-based methods, the most represented techniques apply traditional content-based IR mechanisms; second most frequent are semantic approaches using ontologies or semantic similarity measures; and the third emergent ones are those based on knowledge graphs. A minority of methodsapplies fuzzy rule inference or other heuristic; graph-based models; topic detection and classification; and, finally, a few approaches are defined within the relational and the fuzzy relational DBMSs.

Data-driven approaches are divided among those based on clustering or classification algorithms like K-means, fuzzy c-means, Expectation Maximization, K-Nearest Neighbour, Random Forest, Naive Bayes, and Latent Dirichlet Allocation and those that apply embedding to encode queries, documents, etc.; some proposals apply attention mechanisms, among which BERT transformer to encode documents and queries; a few adopt RNN and LSTM mainly for time series, like speech, and convolutional neural networks (CNN) mainly for images. Among the hybrid approaches there are meta-search agents, applying some model-based techniques and either neural networks or clustering algorithms.

3.7. Type of System and Perceptiveness

Most types of systems are Question Answering systems; second, we have approaches dealing with Community Question Answering; third, are approaches on Knowledge-based systems or expert systems; finally, IRS/passage Retrieval systems and DBMSs complete the top-5.

With respect to perceptiveness, intended as the ability of providing keenness of insight, we considered intuition and easiness of query formulation and answer understanding. Besides, for its applicative and normative relevance, we considered the explicability of the process, intended as providing either local explanations, i.e., meant to understand the criteria and conditions that generated the answers in relation to both the user query and the available data, or global explanations, intended as the interpretability of the whole decision process. This last characteristic is generally satisfied by model-based approaches, "by definition", and is more challenging for data-driven approaches. Finally, the reproducibility of the process was considered, which requires the model implementation and evaluation on data collections which are released freely together with the source code. While we observed that more than half of the approaches present easiness of query formulation, a smaller number produces/yields a result which is easy to understand. Finally, a minority of the approaches are explainable, while half are reproducible.

4. Challenges for Research on Flexible Query Answering Systems

From both the temporal analysis of the relevant keywords extracted from the selected articles and the semantic analysis of the articles we observed that *model-based approaches* of FQASs have been defined mainly at the beginning of the analysed period. Their "flexibility" is formalized within frameworks suited to represent and manage imperfect information, such as probability theory, possibility theory, fuzzy set theory and their extensions exemplified by intuitionistic fuzzy sets [68]. Their main shared characteristic is to be ex-ante explainable, i.e.,"explainable by design", since they are based on a formal representation of the model. Consequently, they are also ex-post explainable,i.e., humans should be capable to understand the criteria and overall process that yield the results [91].

These methods have more recently encountered an increasing competition from the *data-driven approaches* based on Machine Learning, mainly Deep Learning (DL), that achieved greater effectiveness for IR and question answering in big data context. Data-driven approaches do not explicitly model imperfect information as model-based approaches do, but can handle ambiguous information by exploiting their ability to learn from big data.

Nevertheless, as discussed in the following subsections, data-driven methods actually present some weaknesses, which could be faced by hybridising them with model-based methods to exploit the synergies of both.

4.1. Towards Hybrid Flexible Query Answering Systems

The performance of DL approaches needs to be re-assessed in relation to these main situations: in the case of scarcity of training data, in highly specialised contexts such as the legal domain [150], and for applications demanding a clear explanation of the criteria they apply in order to assess their trust and fairness [22] [5].

In particular, the fairness of DL approaches could be flawed, such as when using words embedding created by training texts that express discrimination according to gender or ethnicity [62], [6]. In this regard a current challenge could be to preliminary mine the training collections for identifying unbalanced opinions relative to facts, people, genre, etc. In addition to fairness of FQASs, in many safety-critical decision making tasks that generally occur in the commercial, ecological, medical and legal domains, both retrieving relevant documents and answering questions must be understood by humans to obtain fidelity and trust [59]. This is mandatory in the European Union's Artificial Intelligence Act [46], [47], in line with the General Data Protection Regulation [48], that limits the application of opaque machine learning techniques for automating decision-making activities affecting people: specifically it introduces a "right to explanation" requiring systems to describe the logic used and to justify the results in order to allow their understanding and, possibly, contest [59]. Considering query answering systems, an important part of the explanation is to show the source(s) applied and how the answer is derived from them. This allows the user to verify the answer through evaluating the reliability and trustworthiness of the source information and how the answer was derived from it. This is virtually only feasible in a model-based deductive approach in which the results of a flexible query can be locally explained by knowing the logic of the retrieval process. To this end, the synergic role of data-driven and model-based FQASs can constitute a challenge: data-driven methods can be used to answer queries, thus taking advantage of their high accuracy for many tasks, while model-based FQAS can be applied for translating/approximating the retrieval process to locally explain why the specific answers were yielded, for example by providing the sources, explaining why the kind of personal user data were used, etc.[54]. Such an approach may be seen as following the surrogate modelling paradigm [50]. The "explanation" should be evaluated by assessing to which extent it is complete and accurate [54], and, last but not least, is understandable by a target user [57]. The target user could be either an administrator of the system, who might want to control and improve the system behaviour; a scientist, who would like to know why and how a given result was obtained; or a decision maker, who needs to know if the system is compliant with regulations. For example, non-experts can find it difficult to interpret the mathematical formalization of all system processes executed to evaluate a query and to yield an answer, like indexing, matching, retrieval, and answer generation, while linguistic explanations of opaque FQAS, for example based on fuzzy decision trees, could help non-experts to understand the logic behind the retrieval or answer [5].

4.2. Big Data issues and challenges

Social media, forum, and Internet of Things involving sensors generate tremendous amounts of heterogeneous data, i.e., big data, which stimulated the development of technologies for managing both textual documents, multimedia contents and real-time time series of measurement data, bringing along a demand for a seamless integration of specialised systems. Systems are no more conceived to suit homogeneous data, but rather to accommodate heterogeneous and multisource collections of data.

Big data are generally recognized to be characterized by high volume, high variety, high velocity and heterogeneous veracity [27]. In order to manage semi-structured data, that do not easily fit a fixed tabular structured data format, novel schemaless database management systems, specifically NoSQL and, more recently, NewSQL have been proposed. In order to efficiently manage big data, such systems rely on a horizontal scaling, in which distributed (cloud) data storage (co)operate as components of a polyglot database, so as to allow the concurrent execution of operations on subsets of data, but at the same time arising novel issues. Hence, the design of multi-source heterogeneous data infrastructures is a new challenge. In facts, efficient distributed indexing and querying of big data *Volumes* in a horizontal scaling architecture [10] requires to efficiently cope with “sharding” [104], distributed bitmap indexing. In the case of querying heterogeneous data sources it is necessary to deal with (transparent) query decomposition as well as to apply data integration techniques to the query answers.

Variety. It is well known that QA in a schema-less database, in general, only supports limited querying facilities (e.g., usually not supporting join operations and ad hoc querying). Since in NoSQL systems it is usually assumed that data availability is a higher priority than data consistency, a challenge is reflecting the eventual consistency that implies eventually correct QA results. To solve this problem, NewSQL [88] introduced advanced distributed transaction processing that currently only works under specific conditions, that is, simple predictable transactions not requiring full database scans, thus bringing along new query answering challenges.

Another challenge is querying both sensor data and multimedia data not solely relying on their metadata, which requires advanced content-based indexing techniques; this implies identifying and representing features of regularities, anomalies, shape, color, objects, scene. In this respect data-driven models (e.g., LSTM, RNN and CNNs) demonstrated super-human accuracy in many tasks, for example in face recognition, but their application can be critical due to the lack of transparency of the models. Futhermore, there are domains such as remote sensing in which the accuracy of these approaches needs to be assessed.

Velocity. In NoSQL systems fast data insertion has been considered a priority so as to avoid wasting time on data transformations to a fixed database schema, or on data integrity checks and transaction processing when new data are available as in data streams. A consequence is that in general query evaluation becomes more complex and time consuming. Nevertheless, Internet of Things and social media applications might also need efficient query execution, in real time or near-real time. Hence, the need for faster query execution techniques in distributed, heterogeneous data environments.

Veracity. Data consistency in large distributed heterogeneous data collections can be only guaranteed under limited circumstances. Moreover, an important issue is trust in data, as bad data propagates to bad data analysis and querying results [14], [96].

A lot of research on query answering is about data quality [101], [13] and data quality frameworks in order to make users aware on the quality of data processing results [35], [130]. This implies reporting to the users the quality of both the data sources and the answers/results of retrieval. These issues together with improving data quality are considered to be important research challenges.

Last, but not least data management also implies considering legal aspects. General Data Protection Regulation (GDPR) [18] requirements demand to guarantee the privacy of user; thus developing techniques like anonymization and pseudonymization can be quite challenging in case of textual data or multimedia data [18].

4.3. Emerging Flexible Query Answering Topics

Based on the results of the network and temporal analysis an emerging application context of FQASs is community based systems: this reflects the increasing popularity of social networks and online communities in the acquisition of knowledge including the idea of crowdsourcing. Natural language is the usual way of communicating in community question answering systems, which combines methods from NLP, IR and database processing [116], [76]. However, in evaluating queries in community based systems, a major issue is to assess the quality and veracity of the answers, by estimating the trust of both the information sources and the responders, and by ascertaining their expertise. Model-based FQASs based on multi-criteria decision making and aggregation operators can be a potential promising approach [40]. Another issue in such contexts is estimating the answers validity that varies in time and space, meaning that the systems have to put an emphasis on the temporal and spatial dimensions.

Another issue is the development of community question answering systems for low-resource languages, such as Arabic and Semitic languages, which have in general lower performances than systems developed for rich-resource languages such as English and Chinese. Cross-lingual text classification and retrieval methods exploiting correlations on distinct language-dependent feature spaces can be a promising research direction to design more effective systems in different languages [99]. Not forgetting the contributions to the field of NLP by leading search engine companies such as Google (just think at the language models based on BERT). Nowadays, the efforts in this area are also motivated by the growing popularity of such services as Amazon Alexa or Google Assistant, and related ideas of an intelligent/smart home which call for effective open-domain and commonsense question answering systems, the development of which requires both annotated data sets, which are costly to produce, and background knowledge.

Another up to date research issue is flexible query answering over Knowledge Graphs (KGQA) [125]. The use of natural language is one of the investigated options: users express their information needs by a NL question and retrieve a concise answer generated by querying an RDF knowledge base. This goal poses the problem of filling the lexical gap by handling queries and answers with the same semantics but differing from a lexical point of view. To this end, recent promising approaches apply neural networks and embedding techniques [126], [138]. Besides, in distributed knowledge based systems, in which local domain ontologies coexist to represent heterogeneous domains, alignments methods must be defined to interpret knowledge from a given peer's point of view by exploiting semantic Web technologies [64].

Finally, in KGQA, while several approaches tackled the issues of answering factual queries, only a few considered answering more complex queries, such as procedural queries, involving "why", asking for reasons, and "how", asking for instructions to solve a task [113].

Current research follows template-based approaches, which aid non-technical users to map their input questions to either manually or semi-automatically created SPARQL query templates [1]. Other approaches automatically extract procedural knowledge from textual documents by applying neural networks and language models. Finally, some approaches aid users in carrying out a specific task by responding to the query interactively, step by step, such as in a Chatbot dialogue [90].

A potential alternative approach is exploiting multimodality in which sequences of images, audio files and videos illustrating or exemplifying the requested procedures are retrieved by leveraging on neural systems' ability of modeling multimodal information sources [69]. In Visual Query Answering (VQA) [7] a NL answer is yielded by the system as a result of evaluating a NL question asking for information on an image content provided as input to the system. This can aid visually-impaired users recognize the content of a scene depicted in an image. To solve such tasks, a few approaches proposed to combine VQA with either RNNs [87] or using a self-attention mechanism [83], [74].

In addition to the use of natural language, an emerging research direction targets other forms of human - computer interaction exploiting users' behavioral data; for instance, systems can interpret human communication signals by tracking human movements such as eye blinks, physical movements, facial expressions, query click-through logs, etc. [15] in order to recognize human emotions, like satisfaction, impatience and disappointment of query results [123], [146].

Finally, answering queries which involve geographic entities or concepts and that require evaluating spatial operations modeling different scales is still a relevant task [56].

Query answering systems generally lack proper geographic representations of both entities and spatial relationships, whose meaning is generally vague. Thus, current challenges are the ability to deal with the variability and context dependent meaning of linguistic terms; the ability to exploit several sources of data with distinct resolution; and, finally, the ability to be robust in handling the vagueness and uncertainty of geographic information and relationships [89].

Context plays an important role in QA, not only with respect to geographic searches. Admittedly it is not a new topic in QA (cf., e.g.,[19], [92]) but there are surely new avenues which should be explored, in particular with the use of a more flexible understanding of the very notion of context. Relevance of a search result may depend on external factors such as the location of the user, the time a query is posed, and the history of other queries posed within the same session etc. It may, however, also non-trivially depend on the internal aspects of the search, i.e., on the content of the data source. In the database querying framework, good examples of approaches providing means for taking into account such an internal context are queries with the skyline operator [20] and, a more general approach related to Chomicki's preference queries [34]. Another example of such an approach are contextual bipolar queries [144] and some newer approaches in this vein including [145], in which more flexible understanding of the sophisticated context considered within analytic queries is proposed, and [143], proposing a new idea of searching for a context.

5. Conclusions

In this paper we carried out a critical and comprehensive top-down and a bottom-up analysis of recent developments and proposals of research on FQASs to trace future developments. Our approach was based on the use of novel, network-based methods for the analysis, visualization and summarization of recently published, and relevant literature on Flexible Query Answering [102]. This analysis has provided insight into the state-of-the-art, trends, new proposals and future directions of research in the field.

Flexible query and question answering systems can nowadays access and manage heterogeneous big data that are dynamically changing in time: just think at social networks and forums, at the users' query history, click-through interactions and more generally users' behaviour. Such aspects lead to new trends in question and query answering systems as outlined in the following.

Novel indexing methods for big data have been defined to optimise indexes and at the same time to cope with semantic relationships linking terms and concepts (synonymous, Hieronymus, etc.). To this end, embedding methods have emerged to allow reducing the representation space while identifying semantic relationships between terms.

The state-of-the-art methods for both relevant documents' ranking to user queries, and for recommending documents based on user models and preferences inferred from user interaction data, have gradually changed from model-based approaches towards *data-driven approaches*, employing attention mechanisms and transformers in which target collections of query-answers are exploited for deriving models, as it happened in image object detection [3].

The success of data-driven approaches further stimulated the *creation of specialised question - answer benchmark corpora* for the most diverse tasks, to be used to both train the data-driven models and to test their effectiveness (cf., e.g., [12]).

Nevertheless, these recent approaches raise novel needs and challenges which are aimed to cope with some potential weaknesses of data-driven approaches. First of all identifying bias, and unbalanced aspects in benchmark collections in order to be able to generate fair and trustful data-driven FQASs. To this end, a novel role of model-based FQA methods can be to explore the benchmark collections to identify potential pitfalls and biases. Second, defining FQASs compliant with current regulations about explainability of the models and preservation of the user privacy. In this respect model-based FQASs have a chance to be used for providing local explanations of results yielded by data-driven question answering systems, to increase user awareness of both the used sources, and the criteria and personal data used to yield the answer or the recommendation. Finally, there is a change in perspective on FQASs. For a long time they have been regarded as extractive systems [107], which just retrieve information from various external resources, eventually, evaluating the quality and the veracity of both the source and the information, but not constructing answers which require to mine and summarize implicit information from one or several sources. Nowadays, FQASs are not merely considered as looking for relevant information to a user query in either a document collection, a database or a knowledge base; they are conceived as intelligent systems, that are capable to interpret the query and user intent and context to select the trusted information sources, and to retrieve from them, analyse, summarize and appropriately present to the final user the relevant information (s)he needs. *Graph-based representations and multimodal FQASs*, conceived to detect the preferred means of interaction with the user, are promising scenarios for the future.

On the one side, knowledge-graphs represent concepts and their interrelationship. On the other side, multimodal systems regenerate the information presented in different media in such a way as to support both the formulation of the user query and the understanding of the results using multiple sensory and response modalities [75]. In this respect, the role of the emerging virtual reality technologies, capable to generate metaverse providing immersive experiences to users can be a challenge for future interactions in social networks, for 3D product recommendations, for virtual routing and path recommendations, and spatial queries result exploration by enabling interaction in 3D scenes [44].

Concluding this paper, the results of the semantic analysis, the reflections and discussion helped us to gain a deep view of the FQAS research field, by identifying new trends and promising research directions. In this sense the paper can hopefully play a crucial role for shaping the further developments of FQASs and related topics.

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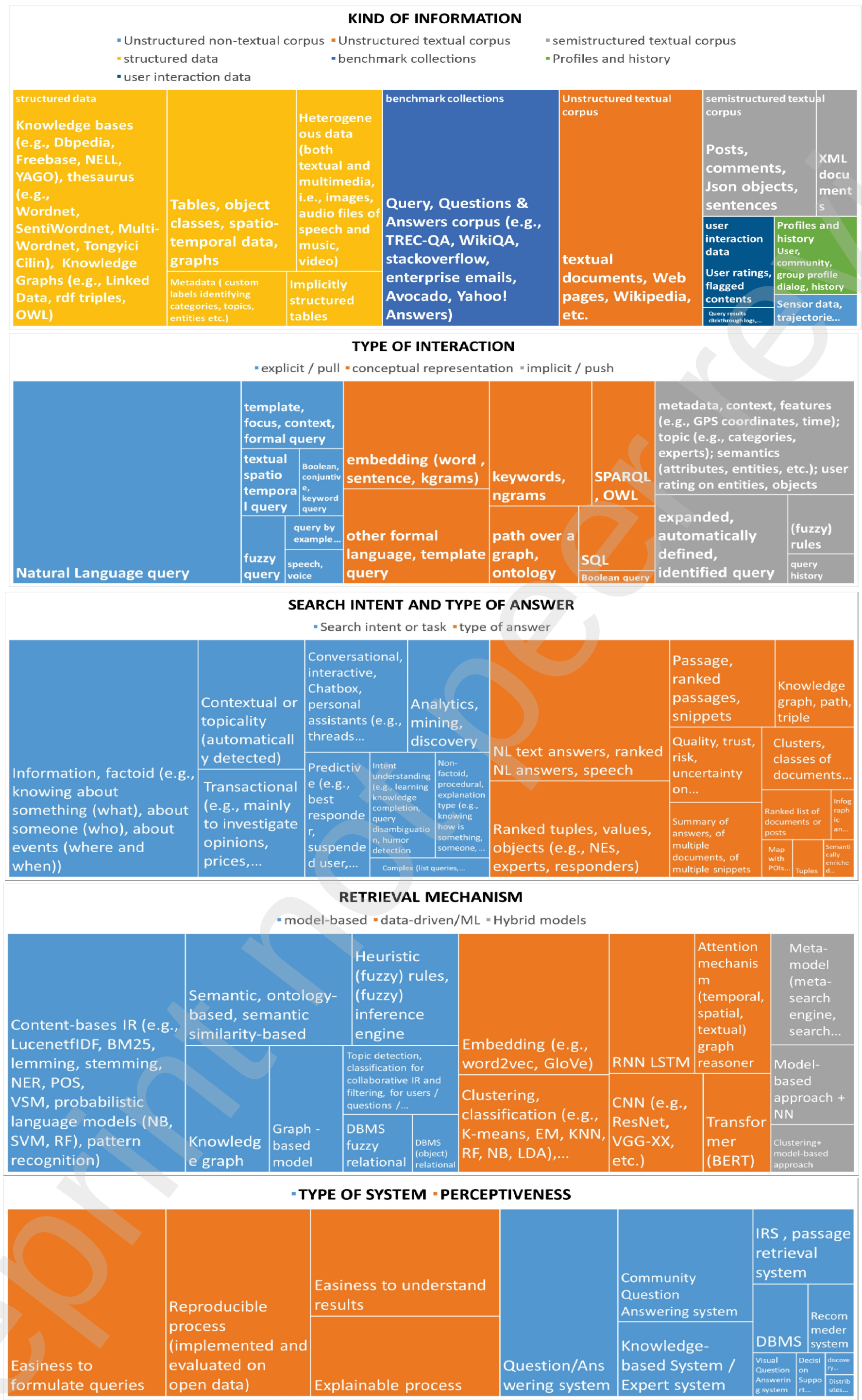
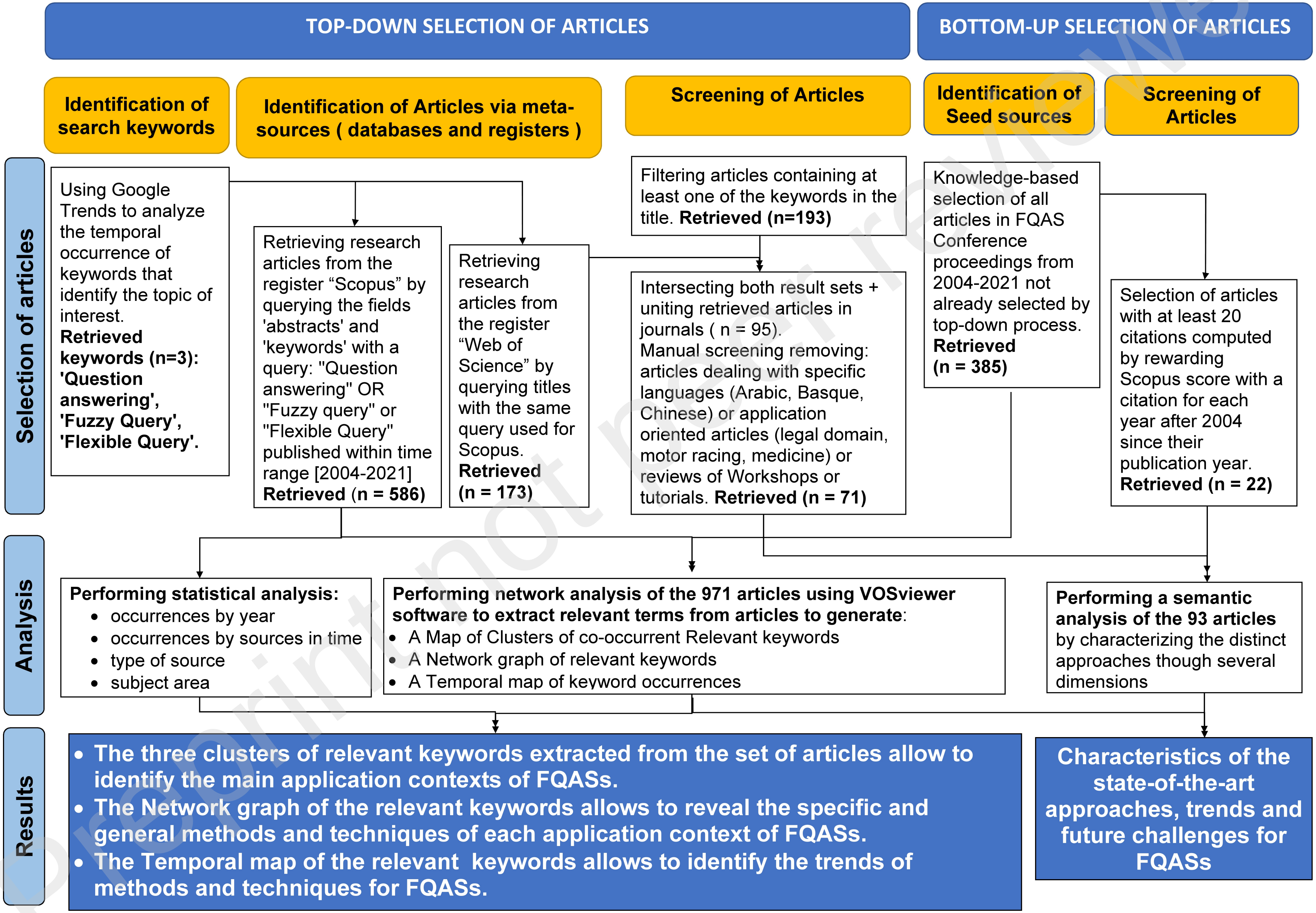


Figure 4: Tree maps representing for each semantic dimension the categories of the proposals in the 93 selected articles.

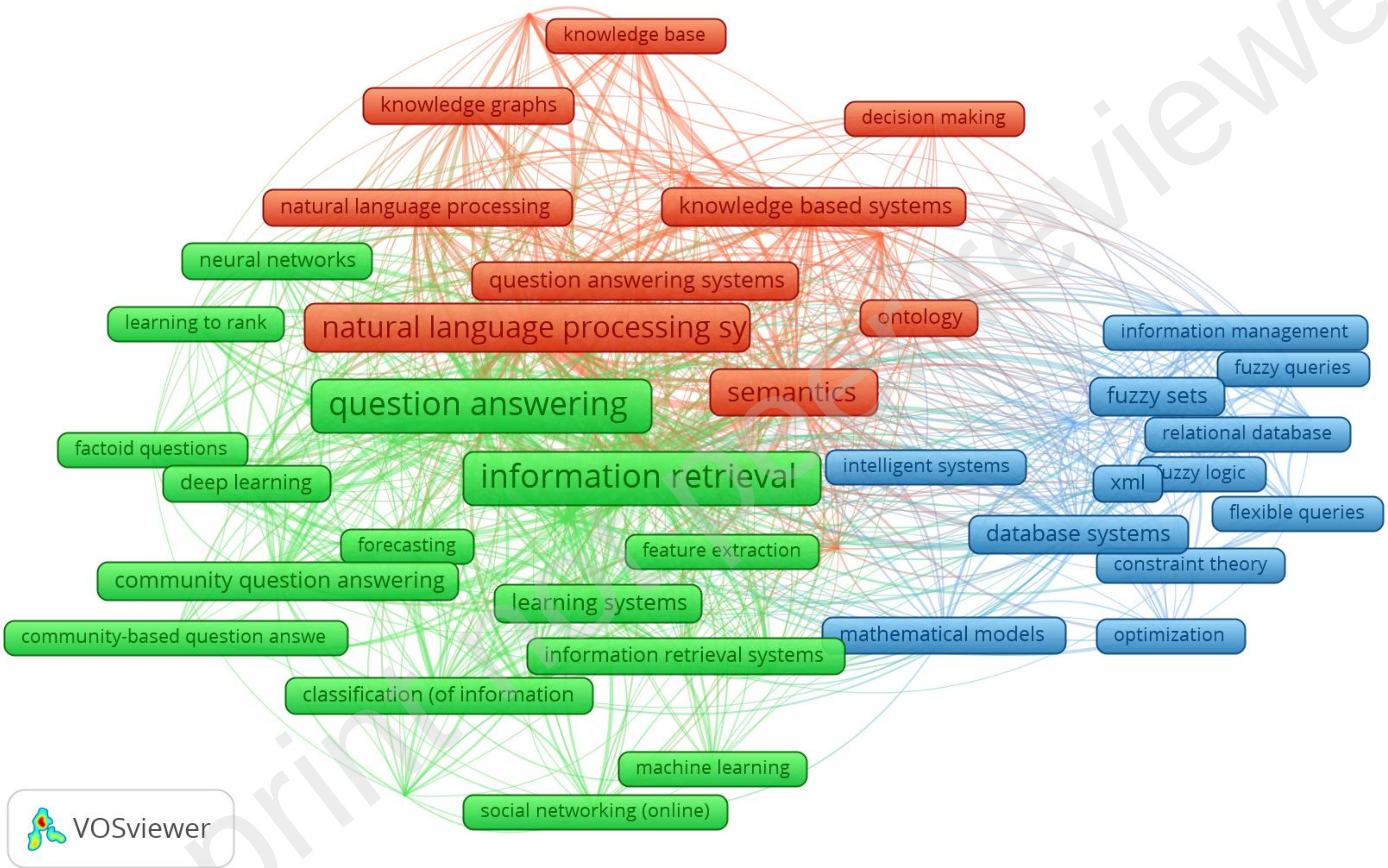
PRISMA 2020 flow diagram revisited

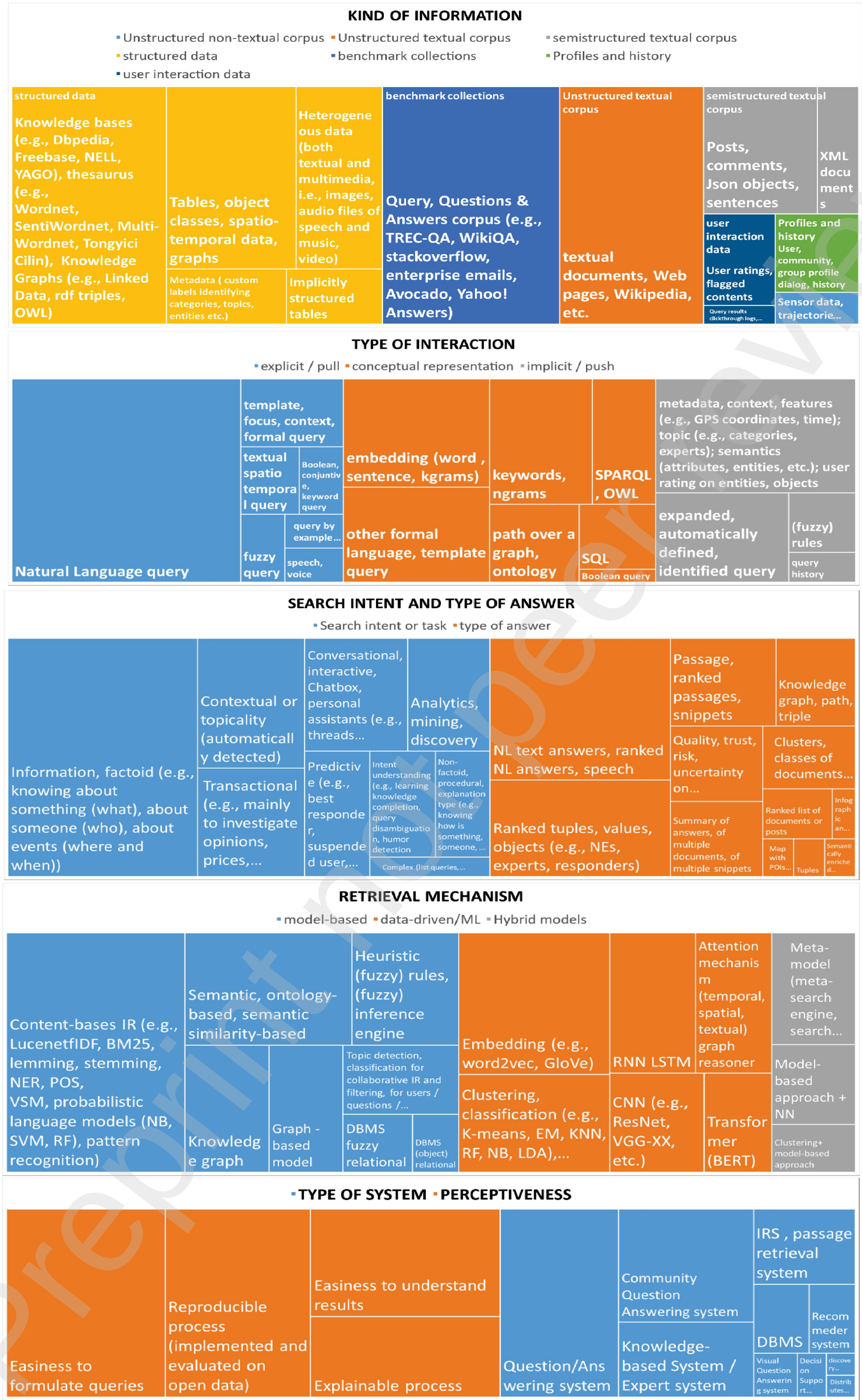


The power and potentials of Flexible Query Answering Systems: a critical and comprehensive analysis

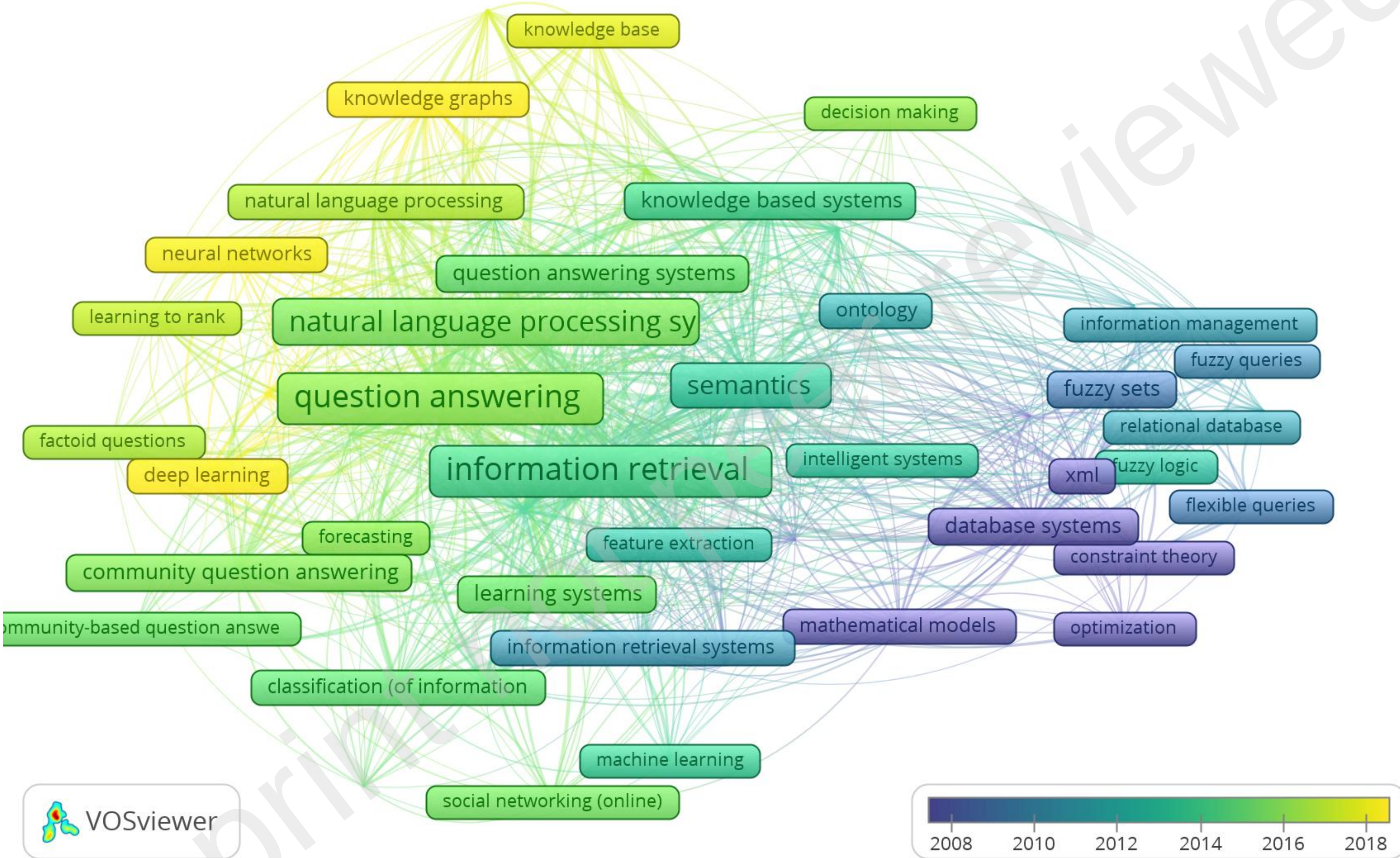
Troels Andreasen, Gloria Bordogna, Guy De Tr´e, Janusz Kacprzyk, Henrik
Legind Larsen, Slawomir Zadro˙zny

- Top-down and Bottom-up analysis of research literature on Flexible Query Answering Systems (FQASs) compliant with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines;
- Network and temporal Analysis of Bibliographic data on Flexible Query Answering Systems to reveal main application contexts, main methods, interrelations, and temporal trends;
- Semantics classification of approaches with respect to types of information dealt with, types of queries and answers, types of systems, implementations characteristics etc;
- Identification of recent trends and future challenges for the FQA field;


knowledge base
knowledge graphs
decision making
natural language processing
knowledge based systems
neural networks
question answering systems
learning to rank
natural language processing sy
ontology
information management
fuzzy queries
fuzzy sets
question answering
semantics
relational database
factoid questions
intelligent systems
fuzzy logic
xml
deep learning
information retrieval
flexible queries
forecasting
feature extraction
database systems
constraint theory
community question answering
learning systems
community-based question answe
mathematical models
optimization
information retrieval systems
classification (of information
machine learning
social networking (online)
VOSviewer



KIND OF INFORMATION
Unstructured non-textual corpus
Unstructured textual corpus
semistructured textual corpus
structured data
benchmark collections
Profiles and history
user interaction data
structured data
Knowledge bases (e.g., Dbpedia, Freebase, NELL, YAGO), thesaurus (e.g., Wordnet, SentiWordnet, Multi-Wordnet, Tongyici Cilin), Knowledge Graphs (e.g., Linked Data, rdf triples, OWL)
Tables, object classes, spatio-temporal data, graphs
Heterogeneous data (both textual and multimedia, i.e., images, audio files of speech and music, video)
Metadata (custom labels identifying categories, topics, entities etc.)
Implicitly structured tables
benchmark collections
Query, Questions & Answers corpus (e.g., TREC-QA, WikiQA, stackoverflow, enterprise emails, Avocado, Yahoo! Answers)
Unstructured textual corpus
textual documents, Web pages, Wikipedia, etc.
semistructured textual corpus
Posts, comments, Json objects, sentences
XML documents
user interaction data
User ratings, flagged contents
Profiles and history
User, community, group profile dialog, history
Sensor data, trajectorie...
TYPE OF INTERACTION
explicit / pull
conceptual representation
implicit / push
Natural Language query
template, focus, context, formal query
textual spatio temporal query
Boolean, conjuntive, keyword query
query by example...
fuzzy query
speech, voice
embedding (word , sentence, kgrams)
keywords, ngrams
SPARQL , OWL
other formal language, template query
path over a graph, ontology
SQL
Boolean query
metadata, context, features (e.g., GPS coordinates, time); topic (e.g., categories, experts); semantics (attributes, entities, etc.); user rating on entities, objects
expanded, automatically defined, identified query
(fuzzy) rules
query history
SEARCH INTENT AND TYPE OF ANSWER
Search intent or task
type of answer
Information, factoid (e.g., knowing about something (what), about someone (who), about events (where and when))
Contextual or topicality (automatically detected)
Transactional (e.g., mainly to investigate opinions, prices,...
Conversational, interactive, Chatbox, personal assistants (e.g., threads...
Analytics, mining, discovery
Predictive (e.g., best responder, suspended user,...
Intent understanding (e.g., learning knowledge completion, query disambiguation, humor detection
Non-factoid, procedural, explanation type (e.g., knowing how is something, someone, ...
Complex (list queries,...
NL text answers, ranked NL answers, speech
Ranked tuples, values, objects (e.g., NEs, experts, responders)
Passage, ranked passages, snippets
Knowledge graph, path, triple
Quality, trust, risk, uncertainty on...
Clusters, classes of documents...
Summary of answers, of multiple documents, of multiple snippets
Ranked list of documents or posts
Infographic an...
Map with POIs...
Tuples
Semantically enriched...
RETRIEVAL MECHANISM
model-based
data-driven/ML
Hybrid models
Content-bases IR (e.g., LucenetfIDF, BM25, lemming, stemming, NER, POS, VSM, probabilistic language models (NB, SVM, RF), pattern recognition)
Semantic, ontology-based, semantic similarity-based
Heuristic (fuzzy) rules, (fuzzy) inference engine
Topic detection, classification for collaborative IR and filtering, for users / questions /...
Knowledge graph
Graph - based model
DBMS fuzzy relational
DBMS (object) relational
Embedding (e.g., word2vec, GloVe)
RNN LSTM
Attention mechanism (temporal, spatial, textual) graph reasoner
Clustering, classification (e.g., K-means, EM, KNN, RF, NB, LDA),...
CNN (e.g., ResNet, VGG-XX, etc.)
Transformer (BERT)
Meta-model (meta-search engine, search...
Model-based approach + NN
Clustering+ model-based approach
TYPE OF SYSTEM
PERCEPTIVENESS
Easiness to formulate queries
Reproducible process (implemented and evaluated on open data)
Easiness to understand results
Explainable process
Question/Answering system
Community Question Answering system
Knowledge-based System / Expert system
IRS , passage retrieval system
DBMS
Recommender system
Visual Question Answering system
Decision Support...
discovery...
Distributes...


knowledge base
knowledge graphs
decision making
natural language processing
knowledge based systems
neural networks
question answering systems
learning to rank
natural language processing sy
ontology
information management
fuzzy queries
semantics
fuzzy sets
question answering
relational database
factoid questions
intelligent systems
fuzzy logic
deep learning
information retrieval
xml
flexible queries
database systems
forecasting
feature extraction
constraint theory
community question answering
learning systems
mmunity-based question answe
mathematical models
optimization
information retrieval systems
classification (of information
machine learning
social networking (online)
VOSviewer
2008
2010
2012
2014
2016
2018

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: