Question Answering Using Structured and Unstructured Data

Doctoral thesis proposal

Denis Savenkov

Dept. of Math & Computer Science

Emory University

denis.savenkov@emory.edu

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Abstract

Question answering (QA) research has come a long way from closed domain small systems to IBM Watson, who defeated best human competitors on the Jeopardy! TV show. However, an ultimate human assistant, who can automatically answer all kinds of questions one have is still just a dream. Over the year of research most efforts were put on factoid questions, which can be answered with a short phrase, *e.g.* an entity name, date, number, etc. Modern QA systems employ a variety of different unstructured (text-corpora), semi-structured (tables, Wikipedia infoboxes, question-answer pairs) and structured (databases, knowledge bases) data sources to generate candidate answers. Each of the data sources has its own advantages and limitations, in particular a text fragment encodes very limited amount of information about the entities involved in the statements, which complicates the reasoning about the answer correctness. For example, most factoid QA systems tries to substitute missing information with a prediction, *i.e.* predict an expected lexical answer type (LAT) from the question and match it against the also predicted answer entity type. On the other side of the spectrum knowledge bases (KB) aggregate all available information about entities and support effective querying with a structured query language, such as SPARQL. The problem comes when we need to translate natural language information need to a structured query. Modern knowledge base question answering (KBQA) systems use question-answer pairs (QnA), question paraphrases and other resources to learn a lexicon to map from natural language phrases to knowledge base objects, which is still limited and works well for relatively popular simple questions. In addition knowledge bases are inherently incomplete and many entities, predicates and facts are simply missing. Therefore, it make sense to combine different data sources for question answering, and this approach was already shown to be successful by systems such as IBM Watson, but they treat different data sources mostly independently and use them to produce as a set of candidates, which are then ranked and the best answer is selected. In my dissertation I propose to consider unstructured textual and structured knowledge base resources, connected via entity linking, together for joint reasoning on the candidate generation stage. Existing datasets for question answering are either relatively small (QALD tasks), focused on text (TREC QA) or on knowledge bases only (*e.g.* WebQuestions). To evaluate the approach I'm going to build a new realistic dataset extracted from Yahoo! Answers question-answer pairs.

Beyond factoid questions we have a plethora of different information needs, that require more than a simple fact to answer. Such questions are usually called non-factoid and more and more research effort is devoted to answering such questions. In 2015 Text REtrieval Conference (TREC) pioneered LiveQA shared task track, which targets automatic question answering of various types of questions user post on Yahoo! Answers Community Question Answering (CQA) website. Existing research has demonstrated the effectiveness of reusing answers to similar previously posted questions, but in many cases such questions are not available or challenging to find. Alternatively, existing systems rank passages extracted from regular web pages. However, ranking is complicated due to the lexical gap between question and answer text. Knowledge about what question does a paragraph of text answers would be very useful signal for ranking, which is supported by the results of the winning TREC LiveQA approach. In my thesis I propose to make a step further and automatically extract candidates text passages along with questions which they answers. This can be done by automatically detecting question-answer pairs from certain web pages (*e.g.* forums, FAQ, *etc.*). In addition, we can build upon the recent success with automatic text generation by recurrent neural networks and train a model to predict a question for a given text fragment.

In summary, this dissertation aims to improve the performance of automatic question answering systems for both factoid and non-factoid question answering.

Contents

1 Introduction

1.1 Motivation

The ability to answer user questions with precise and concise information is a hard problem with a long history of research. Various data sources are available for candidate answer generation, two major ones are unstructured text corpora, and structured knowledge bases (e.g. dpPedia [6] and Freebase [15]). A hybrid approach to question answering [9, 37] generates candidates from multiple sources, however each of them is typically processed separately and results are merged on the scoring and ranking stage when some information is already lost. Efficient combination of different information sources has potential to improve both text and knowledge base question answering systems. I propose to combine all the available sources together and do joint reasoning to generate better answer candidates and improve the overall question answering performance.

Question answering from text corpora typically starts by retrieving a set of potentially relevant documents using the question (or some transformation of the question [1]) as the query, and then extracting entities, phrases, sentences or paragraphs believed to be the answer to the question. However, the information available in the retrieved pieces of text is very limited and often not enough to decide whether it can be the answer to the given question. For example, below is one of the questions from TREC QA 2007 dataset:
"What republican senators supported the nomination of Harriet Miers to the Supreme Court?"
A candidate answer sentence *"Minority Leader Harry Reid had already offered his open support for Miers."* mentions a senator "Harry Reid" and clearly says about his support of the nomination. However, "Harry Reid" is not a correct answer to the question because he is a member of the Democratic party. This information is not available in the answer candidate sentence, but it is present as one of the properties in Freebase: [Harry Reid, political_party, Democratic party][1]. Therefore, by looking into the knowledge available about the mentioned entities a QA system can make a better judgment about the candidate answer.

Question answering over linked data (knowledge bases) converts a natural language question into a structured query, such as SPARQL. The main challenge for such systems is to map words and phrases from the question to the corresponding entities and predicates from a KB. Usually, such lexicon is built during training using ground truth question-query pairs [25] or question-answer pairs [10]. Improvements were made by extending the lexicon using Wikipedia and patterns expressing certain predicates obtained via distant supervision [7, 16, 69, 84, 105]. But still, the amount of available labeled or weakly labeled training data is much smaller than the amount of unstructured data. This unstructured data will complement the learned lexicon, e.g. even if a question about a certain predicate wasn't seen during training, a set of text paragraphs mentioning both of the related entities can provide a QA system with enough evidence to make the correct decision.

Table 1.1 lists pros and cons of structured and unstructured data sources for factoid and non-factoid question answering.

[1] Actually, in Freebase the entities are connected by a path of length 2 through a mediator node. The predicates on the path are: /government/politician/party and /government/political_party_tenure/party

Table 1.1: Pros and cons of structured and unstructured data sources for factoid and non-factoid question answering

	unstructured data	structured data
factoid questions	Text + easy to match against question text + cover a variety of different information types - each text phrase encodes a limited amount of information about mentioned entities	Knowledge Bases + aggregate all the information about entities allow complex queries over this data using special languages (e.g. SPARQL) - hard to translate natural language questions into special query languages - KBs are incomplete (missing entities, facts and properties)
non-factoid questions	Text + contain relevant information to a big chunk of user needs - hard to extract semantic meaning of a paragraph to match against the question (lexical gap)	Question-Answer pairs + easy to find a relevant answer by matching the corresponding questions - cover a smaller subset of user information needs

The main focus of research in automatic question answering was on **factoid questions**, which inquire about a certain fact and can be answered with a short phrase, such as an entity name, date or number. Such questions cover, although big and an important, but only a fraction of user information needs. Questions that don't fall into this category are usually referred to as **non-factoid**.

1.2 Research Questions

1.3 Research Plan

1.3.1 Step 1 (Chapter 3)

1.3.2 Step 2 (Chapter 4)

1.3.3 Step 3 (Chapter 5)

1.3.4 Research Timeline

1.4 Contributions and Implications

The key contributions of the proposed research are: 1. New hybrid KB-text question answering algorithm, that is based on graph search, which includes both KB links as well as text search edges to follow. 2. New labelled dataset for question answering (???) 3. New features for ranking answer candidates ???

2 Related Work

The field of automatic questions answering has a long history of research and dates back to the days when the first computers appear. By the early 60s people have already explored multiple different approaches to question answering and a number of text-based and knowledge base QA systems existed at that time [75, 76]. In 70s and 80s the development of restricted domain knowledge bases and computational linguistics theories facilitated the development of interactive expert and text comprehension systems [5, 74, 96, 95]. The modern era of question answering research was motivated by a series of Text Retrieval Conference (TREC[1]) question answering shared tasks, which was organized annually since 1999 [87]. A comprehensive survey of the approaches from TREC QA 2007 can be found in [28]. An interested reader can refer to a number of surveys to track the progress made in automatic question answering over the years [44, 4, 90, 53, 67, 3, 41].

The main focus of research in automatic question answering was on factoid questions. However, recently we can observe an increased interest in non-factoid question answering, and as an indicator in 2015 TREC started a LiveQA shared task track[2], in which the participant systems had to answer various questions coming from real users of Yahoo! Answers[3] in real time.

In the rest of the chapter I will describe related work in factoid (Section 2.1) and non-factoid (Section 2.2) question answering with the focus on data sources used.

2.1 Factoid question answering

Since the early days of automatic question answering researches explored different sources of data, which lead to the development of two major approaches to factoid question answering: text-based (TextQA) and knowledge base question answering (KBQA) [75]. We will first describe related work in TextQA (Section 2.1.1), then introduce KBQA (Section 2.1.2) and in Section 2.1.3 present existing techniques for combining different information sources together.

2.1.1 Text-based question answering

A traditional approach to factoid question answering over text document collections, popularized by TREC QA task, starts by querying a collection with possibly transformed question and retrieving a set of potentially relevant documents, which are then used to identify the answer. Information retrieval for question answering has certain differences from traditional IR methods [52], which are usually based on keyword matches. A natural language question contains certain information, that is not expected to be present in the answer (*e.g.* the keyword who, what, when, *etc.*), and the answer statement might use language that is different from the question (lexical gap problem). On the other side, there is a certain additional information about expected answer statement, that a QA system might infer from the question (*e.g.* we expect to see in a number in response to the "how many" question). One way to deal with this problem is to transform the question in certain

[1] http://trec.nist.gov

[2] http://trec-liveqa.org/

[3] http://answers.yahoo.com/

ways before querying a collection [1, 20]. Raw text data might be extended with certain semantic annotations by applying part of speech tagger, semantic role labeling, named entity recognizer, *etc.* . By indexing these annotations a question answering system gets an opportunity to query collection with additional attributes, inferred from the question [14, 107].

The next stage in TextQA is to select sentences, that might contain the answer. One of the mostly used benchmark datasets for the task, proposed in [92], is based on TREC QA questions and sentences retrieved by participating systems[4]. The early approaches for the task used simple keyword match strategies [49, 79]. However, in many cases keywords doesn't capture the similarity in meaning of the sentences very well and researches started looking on syntactic information. Syntactic and dependency tree edit distances and kernels allow to measure the similarity between the structures of the sentences [68, 73, 43, 106, 91]. Recent improvements on the answer sentence selection task come are associated with the deep learning techniques, *e.g.* recursive neural networks using sentence dependency tree [50], convolutional neural networks [110, 70], recurrent neural networks [83, 89]. Another dataset, called WikiQA [102], raises a problem of answer triggering, *i.e.* detecting cases when the retrieved set of sentences don't contain the answer.

To provide a user with the concise answer to his factoid question QA systems extract the actual answer phrase from retrieved sentences. This problem is often formulated as a sequence labeling problem, which can be solved using structured prediction models, such as CRF [106], or as a node labeling problem in an answer sentence parse tree [62].

Unfortunately, passages include very limited amount of information about the candidate answer entities, *i.e.* very often it doesn't include the information about their types (person, location, organization, or more fine-grained CEO, president, basketball player, *etc.*), which is very important to answer question correctly, *e.g.* for the question "*what country will host the 2016 summer olympics?*" we need to know that `Rio de Janeiro` is a city and `Brazil` is the country and the correct answer to the question. Therefore, a lot of effort has been put into developing answer type typologies [47, 46] and predicting and matching expected and candidate answer types from the available data [56, 57, 66]. Many approaches exploited external data for this task, I will describe some of this efforts in Section 2.1.3.

Very large text collections, such as the Web, contain many documents expressing the same information, which makes it possible to use a simpler techniques and rely on redundancy of the information. `AskMSR` QA system was one of the first to exploit this idea, and achieved very impressive results on TREC QA 2001 shared task [19]. The system starts by transforming a question into search queries, extracts snippets of search results from a web search engine, and consider word n-grams as answer candidates, ranking them by frequency. A recent revision of the AskMSR QA system [85] introduced several improvements to the original system, *i.e.* named entity tagger for candidate extraction, and additional semantic similarity features for answer ranking. It was also observed, that modern search engines are much better in returning the relevant documents for question queries and query generation step is no longer needed. Another notable systems, that used the web as the source for question answering are `MULDER`[55], `Aranea` [59], and a detailed analysis of what affects the performance of the redundancy-based question answering systems can be found in [58].

[4] A table with all known benchmark results and links to the corresponding papers can be found on http://aclweb.org/aclwiki/index.php?title=Question_Answering_(State_of_the_art)

2.1.2 Knowledge base question answering

Earlier in the days knowledge bases were relatively small and contained information specific to a particular domain, *e.g.* baseball statistics [40], lunar geology [96], geography [111]. However, one of the main challenges in KBQA is mapping between natural language phrases to the database concepts, which raises a problem of domain adaption of question answering systems.

Recent development of large scale knowledge bases (*e.g.* dbPedia [6], Freebase [15], YAGO [80], WikiData[5] shifted the attention towards open domain question answering. Knowledge base question answering approaches can be evaluated on an annual Question Answering over Linked Data (QALD[6]) shared task, and some popular benchmark dataset, such as Free917 [26] and WebQuestions [10]. A survey of some of the proposed approaches can be found in [86].

A series of QALD evaluation campaigns has started in 2011, and since then a number of different subtasks have been offered, *i.e.* since QALD-3 includes a multilingual task, and QALD-4 formulated a problem of hybrid question answering. These tasks usually use dbPedia knowledge base and provide a training set of questions, annotated with the ground truth SPARQL queries. The hybrid track is of particular interest to the topic of this dissertation, as the main goal in this task is to use both structured RDF triples and free form text available in dbPedia abstracts to answer user questions.

The problem of lexical gap and lexicon construction for mapping natural language phrases to knowledge base concepts is one of the major difficulties in KBQA. The earlier systems were mainly trained from question annotated with the correct parse logical form, which is expensive to obtain. Such an approach is hard to scale to large open domain knowledge bases, which contain millions of entities and thousands of different predicates. An idea to extend a trained parser with additional lexicon, built from the Web and other resources, has been proposed by [25]. However, most of the parses of the question produce different results, which means that it is possible to use question-answer pairs directly [10]. PARALEX system ([34]) construct a lexicon from a collection of question paraphrases from WikiAnswers[7]. A somewhat backwards approach was proposed in ParaSempre model of [11], which ranks candidate structured queries by first constructing a canonical utterance for each query and then using a paraphrasing model to score it against the original question. Another approach to learn term-predicate mapping is to use patterns obtained using distant supervision [**?**] labeling of a large text corpus, such as ClueWeb [**?**]. Such labelled collections can also be used to train a KBQA system, as demonstrated by [69]. Such an approach is very attractive as it doesn't require any manual labeling and can be easily transfered to a new domain. However, learning from statements instead of question answer pairs has certain disadvantages, *e.g.* question-answer lexical gap and noise in distant supervision labeling. Modern knowledge bases also contain certain surface forms for their predicates and entities, which makes it possible to convert KB RDF triples into questions and use them for training [16]. Finally, many systems work with distributed vector representations for words and RDF triples and use various deep learning techniques for answer selection. A common strategy is to use a joint embedding of text and knowledge base concepts. For example, character n-gram text representation as input to a convolutional neural network can capture the gist of the question and help map phrases to entities and predicates [108]. Joint embeddings can be trained using multi-task learning, *e.g.* a system can learn to embed a question and candidate answer subgraph using question-answer pairs and question paraphrases at the same time ([16]). Memory Networks, developed by the

[5] http://www.wikidata.org

[6] www.sc.cit-ec.uni-bielefeld.de/qald/

[7] https://answers.wikia.com/

Facebook AI Lab, can also be used to return triples stored in network memory in a response to the user question [17]. This approach uses embeddings of predicates and can answer relatively simple questions, that do not contain any constraints and aggregations. To extend deep learning framework to more complex questions, [29] use multi-column convolutional neural network to capture the embedding of the entity path, context and type.

As for the architecture of KBQA systems, two major approaches have been identified: semantic parsing and information extraction. Semantic parsing starts from question utterances and work to produce the corresponding semantic representation, *e.g.* logical form. The model of [10] uses a CCG parser, which can produce many candidates on each level of parsing tree construction. A common strategy is to use beam search to keep top-k options on each parsing level or agenda-based parsing [12], which maintains current best parses across all levels. An alternative information extraction strategy was proposed by [105], which can be very effective for relatively simple questions. A comparison of this approaches can be found in [104]. The idea of the information extraction approach is that for most of the questions the answer lies in the neighborhood of the question topic entity. Therefore, it is possible to use a relatively small set of query patterns to generate candidate answers, which are then ranked using the information about how well involved predicates and entities match the original question.

Question entity identification and disambiguation is the key component in such systems, they cannot answer the question correctly if the question entity isn't identified. Different systems used NER to tag question entities, which are then linked to a knowledge base using a lexicon of entity names [10, 11, 99]. However, NER can easily miss the right span and the whole system would fail to produce the answer. Recently, most of the state-of-the-art system on WebQuestions dataset used a strategy to consider a reasonable subset of token n-grams, each of which can map to zero or more KB entities, which are disambiguated on the answer ranking stage [103, 7, 84]. Ranking of candidates can be done using a simple linear classification model [103] or a more complex gradient boosted trees ranking model [7, 84].

Some questions contain certain conditions, that require special filters or aggregations to be applied to a set of entities. For example, the question "*who won 2011 heisman trophy?*" contains a date, that needs to be used to filter the set of heisman trophy winners, the question "*what high school did president bill clinton attend?*" requires a filter on the entity type to filter high schools from the list of educational institutions, and "*what is the closest airport to naples florida?*" requires a set of airports to be sorted by distance and the closest one to be selected. Information extraction approaches either needs to extend the set of candidate query templates used, which is usually done manually, or to attach such aggregations later in the process, after the initial set of entities have been extracted [84]. An alternative strategy to answer complex questions is to extend RDF triples as a unit of knowledge with additional arguments and perform question answering over n-tuples [109]. In [94] authors propose to start from single KB facts and build more complex logical formulas by combining existing ones, while scoring candidates using paraphrasing model. Such a a template-free model combines the benefits of semantic parsing and information extraction approaches.

2.1.3 Hybrid question answering

A natural idea of combining available information sources to improve question answering has been explored for a long time. WordNet lexical database [63] was among the first resources, that were adapted by QA community [48, 65], and it was used for such tasks as query expansion and definition extraction. Wikipedia[8], which can be characterized as an unstructured and semi-structured (infoboxes) knowledge base, quickly became a valuable resource for answer extraction and verification [2, 21]. Developers of the Aranea QA system noticed that structured knowledge bases are very effective in answering a significant portion of relatively simple questions [59]. They designed a set of regular expressions for popular questions that can be efficiently answered from a knowledge base and fall back to regular text-based methods for the rest of the questions.

One of the major drawbacks of knowledge bases is their incompleteness, which means that many entities, predicates and facts are missing from knowledge bases, which limits the number of questions one can answer using them. One approach to increase the coverage of knowledge bases is to extract information from other resources, such as raw text[64, 51, 42], web tables[22], *etc.* . However, the larger the knowledge base gets, the more difficult it's to find a mapping from natural language phrases to KB concepts. Alternatively, open information extraction techniques ([31]) can be used to extract a surface form-based knowledge base, which can be very effective for question answering. Open question answering approach of [33] combines multiple structured (Freebase) and unstructured (OpenIE) knowledge bases together by converting them to string-based triples. User question can be first paraphrased using paraphrasing model learned from WikiAnswers data, then converted to a KB query and certain query rewrite rules can be applied, and all queries are ranked by a machine learning model.

SPOX tuples, proposed in [100], encode subject-predicate-object triples along with certain keywords, that could be extracted from the same place as RDF triple. These keywords encode the context of the triple and can be used to match against keywords in the question. The method attempts to parse the question and uses certain relaxations (removing SPARQL triple statements) along with adding question keyphrases as additional triple arguments. As an extreme case of relaxation authors build a query that return all entities of certain type and use all other question terms to filter and rank the returned list.

However, by applying information extraction to raw text we inevitably lose certain portion of the information due to recall errors, and extracted data is also sometimes erroneous due to precision errors. In [98], authors propose to use textual evidence to do answer filtering in a knowledge base question answering system. On the first stage with produce a list of answers using traditional information extraction techniques, and then each answer is scored using its Wikipedia page on how well it matches the question. Knowledge bases can also be incorporated inside TextQA systems. Modern KBs contain comprehensive entity types hierarchies, which were utilized in QuASE system of [81] for answer typing. In addition, QuASE exploited the textual descriptions of entities stored in Freebase knowledge base as answer supportive evidence for candidate scoring. However, most of the information in a KB is stored as relations between entities, therefore there is a big potential in using all available KB data to improve question answering.

Another great example of a hybrid question answering system is IBM Watson, which is arguably the most important and well-known QA systems ever developed so far. It was designed to play the Jeopardy TV show[9]. The system combined multiple different approaches, including text-based, relation extraction and knowledge base modules, each of which generated candidate answers, which are then pooled together for ranking and answer selection. The full architecture of the system is well described in [35] or in the full special issue of the IBM Journal of Research and Development [36]. YodaQA [8] is an open source implementation of the ideas behind the IBM Watson system.

[8] http://www.wikipedia.org

[9] https://en.wikipedia.org/wiki/Jeopardy!

2.2 Non-factoid question answering

ANSWER REUSING Some questions on CQA websites are repeated very often and answers can easily be reused, [60] studies different types of CQA questions and answers and analyzes them with respect to answer re-usability. A number of methods for similar question retrieval have been proposed [NAMELY???]. Alignment between question terms can serve as a good indicator of their semantic similarity. Such an alignment can be produced using a machine learning model with a set of features, representing the quality of the match [93]. Alignment and translation models are usually based on term-term similarities, which are often computed from a monolingual alignment corpus. This data can be very sparse, and to overcome this issue [38] proposed higher-order lexical semantic models, which estimates similarity between terms by considering paths of length more than 1 on term-term similarity graph. Monolingual alignment corpora are also limited, however, it's possible to use the discourse relations of sentences in a text to learn monolingual alignment models [72].

Questions often have some metadata, such as category on a community question answering website. This information can be very useful for certain disambiguations, and can be encoded in the answer ranking model [112].

WEB SEARCH BASED RETRIEVAL One of the first non-factoid question answering system was described in [78] and was based on web search using chunks extracted from the original question. The ranking of extracted answer candidates was done using a translation model, which showed better results than n-gram based match score.

RANKING Candidate answer passages ranking problem becomes even more difficult in non-factoid questions answering as systems have to deal with larger piece of text and need to "understand" what kind of information is expressed there. One of the first extensive studies of different features for non-factoid answer ranking can be found in [82], who explored information retrieval scores, translation models, tree kernel and other features using tokens and semantic annotations (dependency tree, semantic role labelling, *etc.*) of text paragraphs.

WebAP is a dataset for non-factoid answer sentence retrieval, which was developed in [101]. Experiments conducted in this work demonstrated, that classical retrieval methods doesn't work well for this task, and multiple additional semantic (ESA, entity links) and context (adjacent text) features have been proposed to improve the retrieval quality.

The structure of the web page, from which the answers are extracted can be very useful. Wikipedia articles have a good structure, and the information encoded there can be extracted in a text-based knowledge base, which can be used for question answering [77].

TREC LIVEQA

Most of the approaches from TREC LiveQA 2015 combined similar question retrieval and web search techniques [97, 71, 88]. Answers to similar questions are very effective for answering new questions [71]. However, we a CQA archive doesn't have any similar questions, we have to fall back to regular web search. The idea behind the winning system of CMU [88] is to represent each answer with a pair of phrases - clue and answer text. Clue is a phrase that should be similar to the given question, and the passage that follows should be the answer to this question.

2.3 User interactions

An interesting approach for knowledge base construction through dialog with the user has been proposed by [45].

A very nice crowdsourcing method to obtain answers to tail information needs was proposed by [13]. Question query-url pairs are first mined from query logs, and then the wisdom of a crowd is used to extract and save answers to these questions.

[18] retrieves Wikipedia statements that support user answers for opinion questions.

2.4 Summary of Related Work

Most previous work in ...

3 Structured and Unstructured Data for Factoid Question Answering

Over the decades of research in factoid question answering, two relatively separate approaches have emerged: text-centric, or Text-QA and knowledge base-centric, or KBQA. Each approach has its own advantages and disadvantages (Table 1.1). Billions of documents on the web contain all kinds of knowledge about the world, which can be retrieved to answer user questions. However, each individual statement includes a very limited amount of information about mentioned entities. On the other side, modern open domain large scale knowledge bases, such as dbPedia[1], YAGO[61], Freebase[2], WikiData[3], etc., contain millions of entities and facts about them, and are quite effective in answering some of the user questions. However, knowledge bases have their own disadvantages:

- knowledge bases are inherently incomplete [30], even the largest existing resources miss a lot of entities, facts and properties, that might be of interest to some users.
- it's quite challenging to translate a natural language question into a structured language, such as SPARQL, to query a knowledge base [10].

One way to improve the situation with knowledge base incompleteness is to extract missing information from other data sources, *e.g.* [23, 24, 30, 31, 42, 54]. In my thesis I focus on one particular data source, that didn't receive enough attention in the relation extraction literature, namely question-answer pairs. Section 3.1 will describe our experiments and results in utilizing this data to improve knowledge base coverage. Unfortunately, relation extraction isn't perfect either and there are both precision and recall losses. Alternatively, in my thesis I propose a new hybrid approach to question answering, which leverages a combination of text and knowledge base data to improve every stage of question answering process (Section 3.2).

3.1 Relation Extraction for Knowledge Base Construction

To tackle the first problem researchers have proposed automatic relation extraction methods, such as [64], which can automatically label sentences, that might express certain KB relation and learn a model to extract these relations. Unfortunately, not all the information available on the web is available in natural language statements. In my thesis I propose a method for automatic relation extraction from question answer pairs, which are available in big numbers on community question answering websites, forums, etc.

3.1.1 Relation extraction from Question-Answer pairs

This is my work from NAACL student research workshop.

[1] http://wiki.dbpedia.org/

[2] http://www.freebase.com

[3] https://www.wikidata.org/

3.1.2 Question-guided relation extraction

The idea is that we can aggregate related questions and relation extraction patterns. When a person asks a question, we retrieve passages and sentences to extract the answer from. Imaging a question is asking a certain property of an entity. If we can retrieve a sentence, that mentions this entity along with a candidate answer, we can build a pattern for relation extraction. This pattern will be connected to the question "template". Likewise, if we already have relation extraction patterns we can boost those that are retrieve in response to the question and save this connection.

Hypothesis:

1. Patterns retrieved in response to the question are better in quality, we can boost them. We can try to verify this on some relation extraction dataset and questions from some query log. We can also try to use some KBQA dataset.

2. Patterns mined for questions should help question answering. This is essentially weak supervision for training knowledge base question answering using text based question answering.

Problems:

- How to extract new predicates? If we have a question, and a sentence is mentioning a pair of non-related entities, how can we make a new one?

- How to deal with more complex questions, that are not simple relations

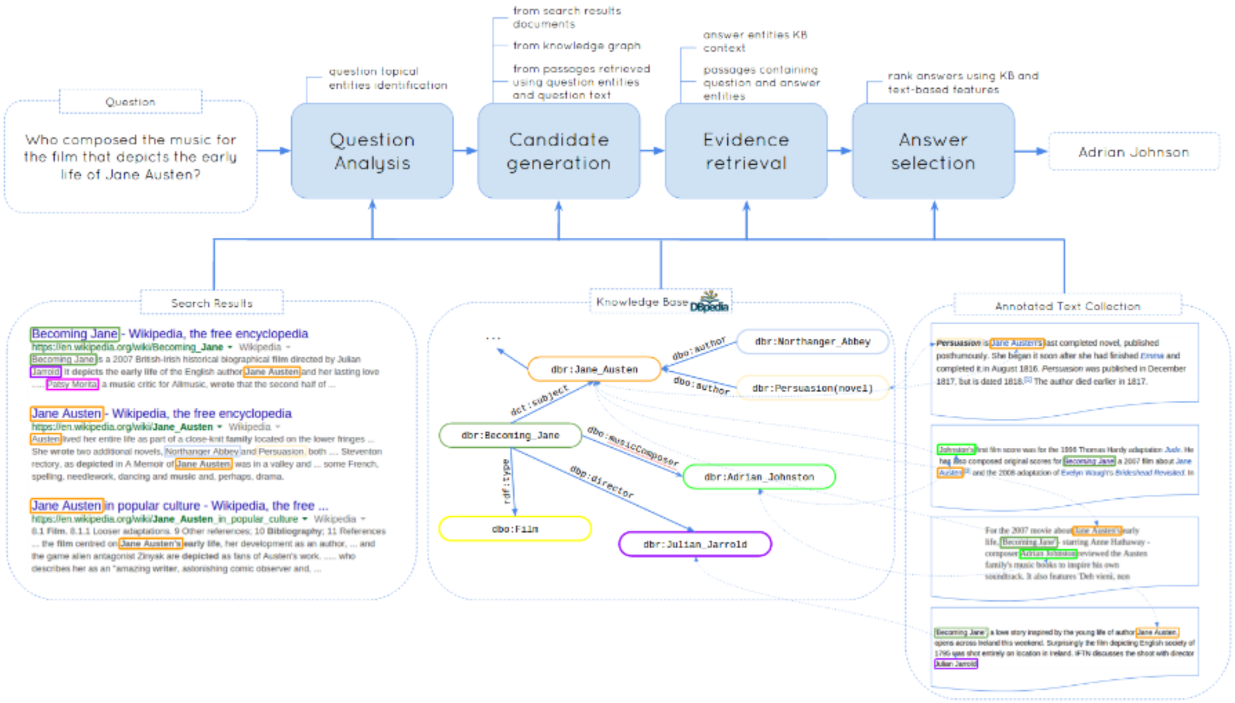
Useful dataset: MSN query log, SimpleQuestions from Facebook, WebQuestions, NYT relation extraction dataset.

This approach can also be applied to open IE. There are sentence selection methods for question answering. We can extract noun phrases (NP mentioned in question and supposedly answer NP), and then aggregate all sentences, that mention the same NPs together. Hypothesis is, that we can extract patterns, that will answer the same question for other entities.

3.2 Semantic Text Annotations for Hybrid Question Answering

Converting unstructured information into structured form by extracting knowledge from text suffers from certain quality losses. Existing relation extraction tools aren't perfect, in particular due to recall losses a lot of information is left behind. Moreover, extractions contain certain level of incorrect information due to precision losses. These errors cap the upper bound on the question answering system performance.

Here I propose to utilize the synergy of structured and unstructured data, and exploit the advantages of each of them to overcome the limitations of the other. More particularly, I propose to annotate and index mentions of knowledge base entities in text documents. Such a representation induces a special kinds of edges to the knowledge base, and allows one to traverse this edges in both directions. These links open up many opportunities for QA reasoning, *e.g.* retrieving all the information about the entity by going from a mention to a KB entity, finding relations between entities by retrieving text passages that mention both of them, extracting candidate evidence by retrieving passages that mention question and answer entities along with some question terms, and so on.


Question
Who composed the music for the film that depicts the early life of Jane Austen?
question topical entities identification
Question Analysis
from search results documents
from knowledge graph
from passages retrieved using question entities and question text
Candidate generation
answer entities KB context
passages containing question and answer entities
Evidence retrieval
rank answers using KB and text-based features
Answer selection
Adrian Johnson
Search Results
Knowledge Base
DBpedia
...
dbr:Jane_Austen
dbo:author
dbr:Northanger_Abbey
dbo:author
dbr:Persuasion(novel)
dct:subject
dbr:Becoming_Jane
dbo:musicComposer
dbr:Adrian_Johnston
rdf:type
dbo:director
dbo:Film
dbr:Julian_Jarrold
Annotated Text Collection

Becoming Jane - Wikipedia, the free encyclopedia
https://en.wikipedia.org/wiki/Becoming_Jane ▾ Wikipedia ▾
Becoming Jane is a 2007 British-Irish historical biographical film directed by Julian Jarrold. It depicts the early life of the English author Jane Austen and her lasting love ..... Patsy Morita, a music critic for Allmusic, wrote that the second half of ...

Jane Austen - Wikipedia, the free encyclopedia
https://en.wikipedia.org/wiki/Jane_Austen ▾ Wikipedia ▾
Austen lived her entire life as part of a close-knit family located on the lower fringes ... She wrote two additional novels, Northanger Abbey and Persuasion, both .... Steventon rectory, as depicted in A Memoir of Jane Austen, was in a valley and ... some French, spelling, needlework, dancing and music and, perhaps, drama.

Jane Austen in popular culture - Wikipedia, the free ...
https://en.wikipedia.org/wiki/Jane_Austen_in_popular_culture ▾ Wikipedia ▾
8.1 Film. 8.1.1 Looser adaptations. 9 Other references; 10 Bibliography; 11 References ... the film centred on Jane Austen's early life, her development as an author, ... and the game alien antagonist Zinyak are depicted as fans of Austen's work. ..... who describes her as an "amazing writer, astonishing comic observer and, ...

Persuasion is Jane Austen's last completed novel, published posthumously. She began it soon after she had finished Emma and completed it in August 1816. Persuasion was published in December 1817, but is dated 1818.[1] The author died earlier in 1817.

Johnston's first film score was for the 1996 Thomas Hardy adaptation Jude. He has also composed original scores for Becoming Jane, a 2007 film about Jane Austen[2] and the 2008 adaptation of Evelyn Waugh's Brideshead Revisited. In

For the 2007 movie about Jane Austen's early life, Becoming Jane - starring Anne Hathaway - composer Adrian Johnston reviewed the Austen family's music books to inspire his own soundtrack. It also features 'Deh vieni, non

Becoming Jane, a love story inspired by the young life of author Jane Austen, opens across Ireland this weekend. Surprisingly the film depicting English society of 1795 was shot entirely on location in Ireland. IFTN discusses the shoot with director Julian Jarrold

Figure 3.1: Architecture of a hybrid factoid question answering system, that uses a combination of structured knowledge base and unstructured text data

3.2.1 Approach

The architecture of the hybrid QA model I propose is presented on Figure 3.1. Here are the main stages of the question answering process:

- **Pre-processing**: identify mentions of KB entities in text document collection and index the documents text and mentions in separate fields
- **Topical entity identification**: search the text collection using question (or reformulated question [1]) as a query and use an approach similar to [27] to detect question topical entities
- **Candidate generation from text**: extract candidate answer (or intermediate answer) entities with evidence from the retrieved text documents using existing techniques, e.g. [85].
- **Candidate generation from KB**: explore the KB neighborhood of question topical entities and entities extracted from text documents on the previous step
- **Candidate generation from KB & Text**: use entity and text index to find entities mentioned near question topical entity and question terms in the document collection
- **KB evidence extraction**: match neighborhood of answer entities (entity type and other entities) against the question to get additional evidence
- **Text evidence extraction**: estimate the similarity between the collection text fragments mentioning question and answer entities and the question text
- **Rank candidate**: rank candidate answers using evidence extracted from the KB as well as from text

Let's consider an example question "*Who composed the music for the film that depicted the early life of Jane Austen?*" from the QALD dataset[4] (Figure 3.1). Even though it's quite easy to identify the "`Jane Austen`" entity in the question, the knowledge base (dbPedia in this example) cannot help us to determine which movie is being referred to. However, there are a lot of documents on the web, that do mention the "`Becoming Jane`" movie and say what is it about. Unfortunately, extracting the name of the composer from these documents is quite challenging, but this task can be easily accomplished by checking the value of the `musicComposer` property in the knowledge base. At the end, for each candidate answer entity, we have all the KB information and passages that mention this entity as evidence to help with the correct answer selection.

3.2.2 Evaluation

Knowledge base QA

I THINK HERE WE CAN INCLUDE OUR RESULTS ON TEXT2KB.

Most of the recent work on knowledge base question answering and semantic parsing have been evaluated on the WebQuestions dataset [10], which contains a collection of question text and correct answer entities. The questions were collected using Google Suggest API and answers crowdsourced using Amazon Mechanical Turk[5] The proposed approach will be compared against the previous results[6] on this dataset. Again, web can be used as a text collection which can be queried using Bing Search API. Relation extraction patterns can be mined using distant supervision from ClueWeb collection using publicly available dataset of Freebase annotations [39].

New factoid question answering dataset. However, WebQuestions dataset has certain limitations, e.g. questions mined using Google Suggest API have very similar structure and lexicon, and to find the answer to the mined questions users were asked to use the question entity Freebase profile page, which only include entities connected directly with a predicate or through a mediator node. Therefore most of the state-of-the-art results on the dataset use a small number of predefined logical form patterns. On the other hand CQA websites have a fraction of factoid questions with provided text answers. Here I propose to use to construct a new dataset for question answering over Freebase by selecting a subset of QnA pairs with at least one entity in question and answer and some reasonable filtering heuristics and manual validation using crowdsourcing (e.g. through Amazon Mechanical Turk). Existing systems need to be retrained and tested on the new dataset to compare against the proposed model.

Text-based QA

WE WILL ANNOTATE TREC DATASETS WITH ENTITIES!!!!

TREC QA datasets served as a benchmark for various question answering systems. Therefore, to evaluate the proposed approach for question answering over text enriched with the structured data I propose to test it on dataset derived from TREC QA and compare against existing strong baselines, including the most related approaches [33, 81]. The proposed system can use the web as the corpus and query it using Bing Search API[7]. Freebase and Reverb extractions [32] are

[4] http://greententacle.techfak.uni-bielefeld.de/ cunger/qald/

[5] http://mturk.com/

[6] http://goo.gl/sePBja

[7] https://datamarket.azure.com/dataset/bing/searchweb

examples of schema-based and open knowledge bases that can be used for the experiments. The metrics used for evaluation typically include accuracy and mean reciprocal rank (MRR).

For non-factoid question answering this year TREC pioneered a new question answering track - TREC LiveQA[8], which targets questions asked by real users of Yahoo! Answers website. This year the deadline for system submission was on August 31 and my system trained on CQA QnA pairs participated in the challenge. The results will be available on the TREC Conference in November 2015. Organizers plan to continue with another TREC LiveQA task next year and this is going to be a good estimation of the effectiveness of the proposed techniques on hard real user questions.

3.3 Summary

In this section we considered two different ways of combining unstructured and structured data to improve factoid question answering. Relation extraction from question-answer pairs aims at filling some gaps in KB fact coverage, whereas semantic annotations of text documents provides a way to incorporate information available in unstructured text documents for reasoning along with KB data to improve the performance of factoid question answering.

Factoid questions represent just a part of user information needs. Many problems require more elaborate response, such as a sentence, list of instructions or in general a passage of text. Such questions are usually referred to as non-factoid questions and they will be the focus of the next Chapter.

[8] http://trec-liveqa.org/

4 Non-factoid Question Answering

Most of the questions that people have are not factoid and cannot be simply answered with a name, date or a number. Typically, such questions require a more elaborate fragment of text as an answer. Traditionally, question answering systems turn to web documents that might contain some relevant passages to be used as an answer.
In this chapter, I summarize the proposed work for improving automatic non-factoid question answering by better understanding the structure of web documents and relationships between their parts and fragments.

4.1 Utilizing the Structure of Web Pages

Non-factoid questions are typically answered with a relatively long paragraph of text[1]. This fact and the nature of questions limits the utility of structured KB resources. One of the main challenges for non-factoid question answering is matching between the question needs and the information expressed in text fragment. Analysis of TREC LiveQA 2015 participants [71] revealed that the quality of answers extracted from previously posted similar questions is typically higher than from regular web passages. Therefore, non-factoid QA system would benefit from the information on which questions does a paragraph of text answer. This information can often be extracted from the structure of a web document, e.g. forum threads, FAQ pages or various CQA websites. Alternatively, we can train a model to predict whether a paragraph answers a given question using titles, subtitles and surrounding text of a web page.

My proposal for non-factoid question answering can be summarized as follows:

- **CQA candidate generation**: retrieve a set of question-answer pairs by searching a CQA archive[2]
- **Web document retrieval**: retrieve a set of documents by querying web search with the question (and queries generated from it)
- **Web candidate answer generation**: classify web page into one of the following types: article, forum thread, FAQ page, CQA page, other. Extract key elements using type-specific extractors (QnA pairs, FAQ and CQA pages, forum question and posts and article passages with the corresponding titles, subtitles and surrounding text).
- **Ranking**: Rank the generated candidate answers by building on techniques from existing research [82].

4.2 Evaluation

LiveQA

[1] TREC LiveQA'15 challenge limits the answer to 1000 characters

[2] https://answers.yahoo.com/

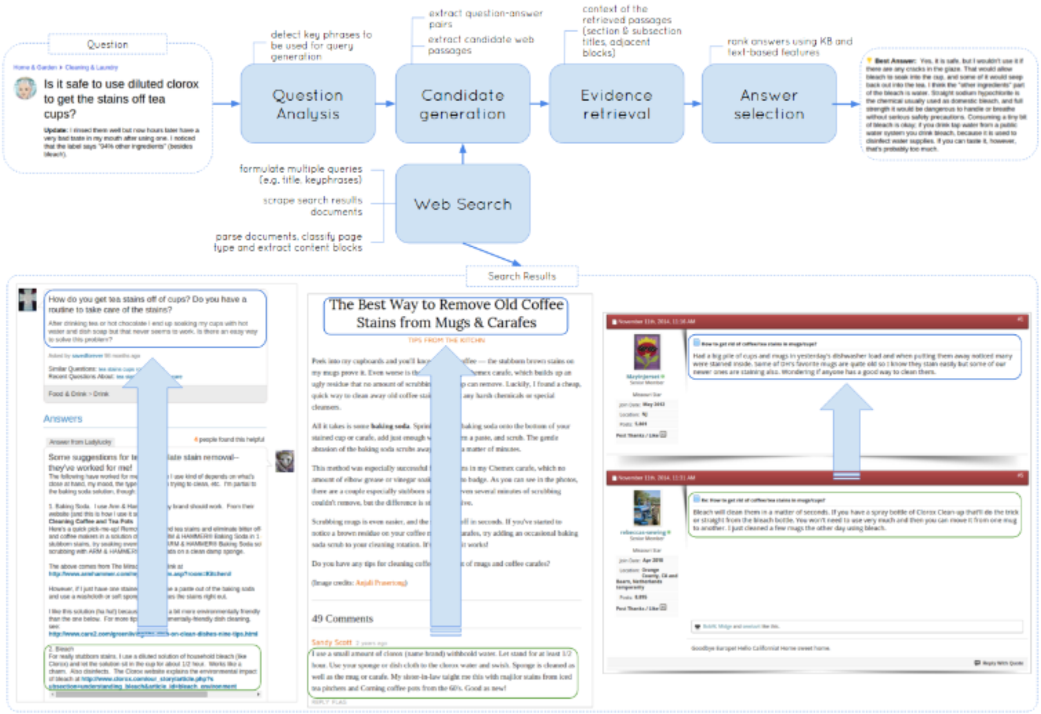

Question
Home & Garden ▸ Cleaning & Laundry
Is it safe to use diluted clorox to get the stains off tea cups?
detect key phrases to be used for query generation
Question Analysis
extract question-answer pairs
extract candidate web passages
Candidate generation
context of the retrieved passages (section & subsection titles, adjacent blocks)
Evidence retrieval
rank answers using KB and text-based features
Answer selection
Best Answer:
formulate multiple queries (e.g. title, keyphrases)
scrape search results documents
parse documents, classify page type and extract content blocks
Web Search
Search Results
How do you get tea stains off of cups? Do you have a routine to take care of the stains?
Answers
The Best Way to Remove Old Coffee Stains from Mugs & Carafes
TIPS FROM THE KITCHEN
49 Comments

Figure 4.1: Using web page structure information for non-factoid question answering

4.3 Summary

5 Users and Question Answering Systems

5.1 Search Hints for Complex Informational Tasks

This is my SIGIR'14 short paper.

5.2 Clarification Questions

This is the work of Pavel Braslavsky.

5.3 Crowd-Sourcing Answers

This is our experiment for LiveQA answer crowdsourcing.

6 Discussion and Implication

The proposed approach targets the problem of improving the performance of question answering systems using joint reasoning over unstructured, semi-structured and structured data sources. By linking entity mentions to their knowledge base objects a text-based QA system will be able to use not only lexical information present in extracted text fragments, but also all the factual information about the entities, which should improve its performance. On the other hand, knowledge base question answering should benefit from textual data about predicates and entities mentioned in a questions and a candidate answer. Additional unstructured data will serve as a bridge between a natural language question and the corresponding knowledge base query, which should boost the recall of question answering systems.

However, there are certain questions and limitations, that I would like to discuss. As we know, knowledge bases are inherently incomplete: not only many facts are missing, but also a set of predicates is far from being complete. Therefore, for many questions there are no corresponding predicates in a knowledge base. Given the fact that at the moment text-based QA systems outperform knowledge base systems on factoid questions from the TREC QA dataset, it is unclear how much additional information a KB can add and how big is an advantage over hybrid approaches that simply combine the candidates obtained from various data sources. An alternative approach to get more knowledge about candidate answers is to retrieve more unstructured data, e.g. previous research found Wikipedia articles to be useful. Another question is related to the usefulness of the information stored in a KB for complex and non-factoid questions. The main challenge is to "understand" the text of the answer and predict whether it replies to the question. Facts stored in Freebase or similar KB might not reveal much about the meaning of the answer and we would need a different source of knowledge.

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