Putting Question-Answering Systems into Practice: Transfer Learning for Efficient Domain Customization

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Traditional information retrieval (such as that offered by web search engines) impedes users with information overload from extensive result pages and the need to manually locate the desired information therein. Conversely, question-answering systems change how humans interact with information systems: users can now ask specific questions and obtain a tailored answer – both conveniently in natural language. Despite obvious benefits, their use is often limited to an academic context, largely because of expensive domain customizations, which means that the performance in domain-specific applications often fails to meet expectations. This paper presents cost-efficient remedies: a selection mechanism increases the precision of document retrieval and a fused approach to transfer learning is proposed in order to improve the performance of answer extraction. Here knowledge is inductively transferred from a related, yet different, tasks to the domain-specific application, while accounting for potential differences in the sample sizes across both tasks. The resulting performance is demonstrated with an actual use case from a finance company, where fewer than 400 question-answer pairs had to be annotated in order to yield significant performance gains. As a direct implication to management, this presents a promising path to better leveraging of knowledge stored in information systems.

CCS Concepts: • Information systems → Question answering; • Social and professional topics → Computing and business;

Additional Key Words and Phrases: Question answering; Machine comprehension; Transfer learning; Deep learning; Domain customization

1 INTRODUCTION

Question-answering (Q&A) systems redefine interactions with management information systems [Lim et al. 2013] by changing how humans seek and retrieve information. This technology replaces classical information retrieval with natural conversations [Simmons 1965]. In traditional information retrieval, users query information systems with keywords in order to retrieve a (ranked) list of matching documents; yet a second step is necessary in which the user needs to extract the answer from a particular document [Belkin 1993; Chau et al. 2008]. Conversely, Q&A systems render it possible for users to directly phrase their question in natural language and also retrieve the answer in natural language. Formally, such systems specify a mapping \((q, D) \mapsto a\) in order to search an answer \(a\) for a question \(q\) from a collection of documents \(D = \{d_1, d_2, \ldots\}\). Underlying this approach is often a two-step process in which the Q&A system first identifies the relevant document \(d_q \in D\) within the corpus and subsequently infers the correct answer \(a \in d_q\) from that document [c.f. Moldovan et al. 2003].

Question-answering systems add several benefits to human-computer interfaces: first, question answering is known to come more naturally to humans than keyword search, especially for those who are not digital natives [c.f. Vodanovich et al. 2010]. As a result, question answering presents a path for information systems that can greatly contribute to the ease of use [Radev et al. 2005] and even user acceptance rates [Giboney et al. 2015; Schumaker & Chen 2007]. Second, Q&A systems promise to accelerate the search process, as users directly obtain the correct answer to their
questions [Roussinov & Robles-Flores 2007]. In practice, this obviates a large amount of manual reading necessary to identify the relevant document and to locate the right piece of information within one. Third, question answering circumvents the need for computer screens, as it can even be incorporated into simple electronic devices (such as wearables or Amazon’s Echo).

One of the most prominent Q&A systems is IBM Watson [Ferrucci 2012], known for its 2011 win in the game show "Jeopardy". IBM Watson has since grown beyond question answering, now serving as an umbrella term that includes further components from business intelligence. The actual Q&A functionality is still in use, predominantly for providing healthcare decision support based on clinical literature.\footnote{IBM Watson for Oncology. https://www.ibm.com/watson/health/oncology-and-genomics/oncology/, accessed January 8, 2018.} Further research efforts in the field of question answering have led to systems targeting applications, for instance, from medicine [e.g. Cao et al. 2011], education [e.g. Cao & Nunamaker 2004] and IT security [Roussinov & Robles-Flores 2007]. However, the aforementioned works are highly specialized and have all been tailored to the requirements of each individual use case.

Besides the aforementioned implementations, question-answering technology has found very little adoption in actual information systems and especially knowledge management systems. From a user point of view, the performance of current Q&A systems in real-world settings is often limited and thus diminishes user satisfaction. The predominant reason for this is that each application requires cost-intensive customizations, which are rarely undertaken by practitioners with the necessary care. Individual customization can apply to, e.g., domain-specific knowledge, terminology and slang. Hitherto, such customizations demanded manually-designed linguistic rules [Kaisser & Becker 2004] or, in the context of machine learning, extensive datasets with hand-crafted labels [c.f. Ling et al. 2017]. Conversely, our work proposes an alternative strategy based on transfer learning. Here the idea is an inductive transfer of knowledge from a general, open-domain application to the domain-specific use case [c.f. Pan & Yang 2010]. This approach is highly cost-efficient as it merely requires a small set of a few hundred labeled question-answer pairs in order to fine-tune the machine learning classifiers to domain-specific applications.

We demonstrate our approach on the basis of a real-world use case from the financial domain. Conventional benchmarks from the literature can answer up to one out of 3.4 questions correctly in the sense that the proposed answer exactly matches the desired word sequence (i.e. not a sub-sequence and no redundant words). Conversely, our system achieves significant performance increases as it bolsters the correctness to one out of 2.0 questions. The gain stems from three components: (1) Transfer learning as our key contribution accounts for a considerable increase in accuracy by 8.1 % to 17.0 %. (2) We show how the use of a simple filter with which users can further restrict their answers to sub-domains can yield additional improvements. (3) We experiment with different neural network architectures for question answering. Altogether, this shows different paths to performance gains.

The remainder of this paper is organized as follows. Section 2 reviews common research streams in the field of question-answering systems with a focus on the challenges that arise with domain customizations. We then develop our strategies for domain customization – namely, selection mechanisms and transfer learning – in Section 3. The resulting methodology is evaluated in Section 4, demonstrating the superior performance over common baselines. Based on these findings, Section 5 discusses implications for the use of Q&A technology in management information systems, while Section 6 concludes.
2 BACKGROUND: QUESTION-ANSWERING SYSTEMS

Recent research on question answering can be divided into two main paradigms according to how these systems reason the response: namely, (i) ontology-based question answering that first maps documents onto entities in order to operate on this alternative representation and (ii) content-based systems that draw upon raw textual input.

2.1 Ontology-Based Q&A Systems

One approach to question answering is to draw upon ontology-based representations. For this purpose, the Q&A system first transforms both questions and documents into ontologies, which are then used to reason the answer. The ontological representation commonly consists of semantic triples in the form of \(<\text{subject}, \text{predicate}, \text{object}>\). In some cases, the representation can further be extended by, for instance, relational information or unstructured data [Xu et al. 2016]. The deductive abilities of this approach have made ontology-based systems especially prevalent in relation to (semi-)structured data such as large-scale knowledge graphs from the Semantic Web [e.g. Berant et al. 2013; Ferrández et al. 2009; Lopez et al. 2007; Unger et al. 2012].

In general, ontology-based Q&A systems entail several drawbacks that are inherent to the internal representation. On the one hand, the initial projection onto ontologies often results in a loss of information [Vallet et al. 2005]. On the other hand, the underlying ontology itself is often limited in its expressiveness to domain-specific entities [c.f. Mollá & Vicedo 2007] and, as a result, the performance of such systems is hampered when answering questions concerning previously-unseen entities. Here the conventional remedy is to manually encode extensive domain knowledge into the system [Maedche & Staab 2001], yet this imposes high upfront costs and thus impedes practical use cases.

2.2 Content-Based Q&A Systems

Content-based Q&A systems operate on raw text, instead of the rather limited representation of ontologies [e.g. Cao et al. 2011; Harabagiu et al. 2000; Radev et al. 2005]. For this reason, these systems commonly follow a two-stage approach [Jurafsky & Martin 2009], as illustrated in Figure 1. In the first step, a module for information retrieval selects the relevant document \(d_q\) from the corpus \(D\) based on similarity scoring. Here the complete content of the original document is retained by using an appropriate mathematical representation (e.g. tf-idf, latent semantic analysis). In the second step, the retrieved documents \(d_q\) are further processed with the help of an answer extraction module that infers

![Diagram of a content-based Q&A system](image)

Fig. 1. Two-stage architecture of a content-based Q&A system. The first stage draws upon functionality from the field of information retrieval in order to identify relevant materials, while the second stage generates the final answer.

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the actual response $a \in d_q$. The latter step frequently draws upon machine learning models in order to benefit from trainable parameters.

Content-based systems overcome several of the weaknesses of ontology-based approaches. First, the underlying similarity matching allows these systems to answer questions that involve out-of-domain knowledge (i.e. unseen entities or relations in question). Second, content-based systems circumvent the need for manual rule engineering, as the underlying rules can be trained with machine learning. As a result, content-based Q&A systems are often the preferred choice in practical settings. We later study how this type facilitates domain customization via transfer learning and how it benefits from advanced deep neural network architectures.

2.2.1 Information Retrieval Module. The first component filters for relevant documents based on the similarity between their content and the query [Jurafsky & Martin 2009]. For this purpose, it is convenient to treat documents as mathematical structures with a well-defined similarity measure. A straightforward approach is to transform documents into a vector space that represents documents and queries as sparse vectors of term or $n$-gram frequencies within a high-dimensional space [Salton 1971]. The similarity between documents and queries can then be formalized as the proximity of their embedded vectors.

In practice, raw term frequencies cannot account for the specificity of terms; that is, a term occurring in multiple documents carries less relevance. Therefore, plain term frequencies have been further weighted by the inverted document frequency, in order to give relevance to words that appear in fewer documents [Sparck Jones 1972]. This tf-idf scheme incorporates an additional normalization on the basis of document length to facilitate comparison [Singhal et al. 1996]. Retrieval based on tf-idf weights is a common choice in Q&A Systems [e.g. Buckley & Mitra 1997; Harabagiu et al. 2000] and has been shown to yield competitive results [Voorhees 2001].

To overcome the limitations of bag-of-words features, state-of-the-art systems take the local ordering of words into account [Chen et al. 2017]. This is achieved by calculating tf-idf vectors over $n$-grams rather than single terms. Since the number of $n$-grams grows exponentially with $n$, one usually utilizes feature hashing [Weinberger et al. 2009] as a trade-off between performance and memory use.

2.2.2 Answer Extraction Module. The second stage derives the actual answer from the selected document. It usually includes separate steps that extract candidate answers and rank these in order to finally select the most promising candidate. We note that some authors also refer to this task as machine comprehension, predominantly when it is used in an isolated setting outside of Q&A systems.

A straightforward approach builds upon the document extracted by the information retrieval module and then identifies candidate answers simply by selecting complete sentences [Richardson 2013]. More granular answers are commonly generated by extracting sub-sequences of words from the original document. These sub-sequences can either be formulated in a top-down process with the help of constituency trees [c.f. Radev et al. 2005; Rajpurkar et al. 2016; Shen & Klakow 2006] or in a bottom-up fashion where $n$-grams are extracted from documents and subsequently combined to form longer, coherent answers [c.f. Brill et al. 2002; Lin 2007].

A common way to rank candidates and decide upon the final answer is based on linguistic and especially syntactic information [c.f. Pasca 2005]. This helps in better matching the type of the information requested by the question (i.e. time, location, etc.) with the actual response. For instance, the question “When did X begin operations?” implies the search for a time and the syntactic structure of candidate answers should thus be fairly similar to expressions involving temporal order, such as “X began operations in Y” or “In year Y, X began operations” [c.f. Kaisser & Becker 2004]. In practice, the procedures of ranking and selection are computed via feature engineering along with machine learning.
classifiers [Echihabi et al. 2008; Rajpurkar et al. 2016; Ravichandran & Hovy 2002]. We later follow the recent approach in [Rajpurkar et al. 2016] and utilize their open-source implementation of feature engineering and machine learning as one of our baselines.

Only recently, deep learning has been applied by [Chen et al. 2017; Wang et al. 2018, 2017a] to the answer extraction module of Q&A systems, where it outperforms traditional machine learning. In these works, recurrent neural networks iterate over the sequence of words in a document of arbitrary length in order to learn a lower-dimensional representation in their hidden layers and then predict the start and end position of the answer. As a result, this circumvents the need for hand-written rules, mixture of classifiers or schemes for answer ranking, but rather utilizes a single model capable of learning all steps end-to-end. Hence, we draw upon the so-called DrQA network from [Chen et al. 2017] as part of our experiments.

Beyond that, we later experiment with further network architectures as part of a holistic comparison. Moreover, the machine learning classifiers inside answer extraction modules are known to require extensive datasets and we thus suggest transfer learning as a means of expediting domain customization.

### 3 METHODS AND MATERIALS

This section describes our proposed Q&A system with domain customization, as well as the benchmarks from prior works against which it is compared. Here we follow the previous literature review and draw upon a content-based system because of its flexibility and performance.

#### 3.1 Information Retrieval Module

The information retrieval module is responsible for locating documents relevant to the given question. Consistent with prior works [c.f. Chen et al. 2017; Wang et al. 2018], documents are represented according to the vector space model [Salton 1971], based on which similarity scores can be computed. Let \( tf_{ji} \) refer to the term frequencies of document \( i = 1, \ldots, N \) for vocabulary \( j = 1, \ldots, T \). In order to better identify characteristic terms, the term frequencies are weighted by the inverse document frequency, i.e. giving the tf-idf score \( w_{ji} = tf_{ji} \cdot idf_j \) [Sparck Jones 1972]. Here the inverse document frequency places additional discriminatory power on terms that appear only in a subset of the documents. It is defined by \( idf_j = \log(N/n_j) \) where \( n_j \) denotes the number of documents that entail the term \( j \). This translates a document \( d_i \) into a vector representation \( d_i = [w_{i1}, w_{i2}, \ldots, w_{iT}]^T \). Analogously, queries are also processed to yield a vector representation \( q \). The previous tf-idf weighting ignores semantics, such as the local ordering of words, and, as a remedy, we incorporate \( n \)-grams instead. Furthermore, we adhere to [Weinberger et al. 2009] and utilize feature hashing in order to improve the time and memory consumption during the construction of document vectors.

The relevance of a document \( d_i \) to a question \( q \) can then be computed by measuring the cosine similarity between both vectors [c.f. Chen et al. 2017; Wang et al. 2018]. This is formalized by

\[
\cos(d_i, q) = \frac{d_i^T q}{\|d_i\| \|q\|}.
\]

Subsequently, the information retrieval module determines the document \( d_q = \arg\min_{d_i} \cos(d_i, q) \) that displays the greatest similarity between document and question.
3.2 Answer Extraction Module

In the second stage, the answer extraction module draws upon the previously-selected document and extracts the answer $a \in d_q$. Based on our literature review, this work evaluates different baselines for reasons of comparability, namely, two benchmarks utilizing traditional machine learning and the DrQA network from the field of deep learning. Furthermore, we suggest the use of two additional deep neural networks that advance the architecture beyond DrQA. More precisely, our networks incorporate character-level embeddings and an interplay of different attention mechanisms, which together allow us to better adapt to unseen words and the context of the question.

3.2.1 Baseline Methods. We implement two baselines from previous literature, namely, a sliding window approach without trainable parameters [Richardson 2013] and a machine learning classifier based on lexical features [Rajpurkar et al. 2016]. Both extract linguistic constituents from the source document to narrow down the number of candidate answers. Here the concept of a constituent refers to one or multiple words that can stand on their own (e.g. nouns, a subject or object, a main clause).

The sliding window approach processes the text passage and chooses the sub-span of words as an answer that has the highest number of overlapping terms with the question. The second approach draws upon a logistic regression in order to rank candidate answers based on an extensive series of hand-crafted lexical features. The choice of features contains, for instance, tf-idf weights extended with lexical information. We refer to [Rajpurkar et al. 2016] for a description of the complete list. The classifier is subsequently calibrated using a training set of documents and correct responses in order to select answers for unseen question-answer pairs.

3.2.2 Deep Learning Methods. Prior work [Chen et al. 2017] has proposed the use of deep learning within the answer extraction module, resulting in the DrQA network, which we utilize as part of our experiments. Furthermore, we draw upon additional network architectures, namely, BiDAF [Seo et al. 2017] and R-Net [Wang et al. 2017b], which were recently developed for the related, yet different, task of machine comprehension. Accordingly, we modify two state-of-the-art machine comprehension models such that they work within our Q&A pipeline. These network architectures incorporate character-level embeddings which allow for the handling of unseen vocabulary and, in practice, find more suitable numerical representations for infrequent words. Second, the attention mechanism is modeled in such a way that it simultaneously incorporates both question and answer, which introduces additional degrees-of-freedom for the network, especially in order to weigh responses such that the context matches.

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\[\text{The task of machine comprehension refers to locating text passages in a given document and thus differs from question answering, which includes the additional search as part of the information retrieval module. These models have shown significant success recently; yet they require the text passage containing the answer to be known up front.}\]
In the following, we summarize the key elements of the different neural networks. The architectures entail several differences across the networks, but generally follow the schematic structure in Figure 2 consisting of embedding layers, encodings through recurrent layers, an attention mechanism for question-answer fusion and the final layer predicting both the start and end position of the answer.

**Embedding layers.** The first layer in neural machine comprehension networks is an embedding layer whose purpose is the replacement of high-dimensional one-hot vectors that represent words with low-dimensional (but dense) vectors. These vectors are embedded in a semantically meaningful way in order to preserve their contextual similarity. Here all networks utilize the word-level embeddings yielded by glove [Pennington et al. 2014]. For both R-Net and BiDAF, additional character-level embeddings are trained to complement the word embeddings for out-of-dictionary words. At the same time, character-level embedding can still yield meaningful embeddings even for rare words with which embeddings at word level struggle due to the small number of samples. Differences between R-Net and BiDAF arise with regard to the way in which character- and word-level embeddings are fed into the next layer. R-Net computes a simple concatenation of both vectors, while BiDAF fuses them with an additional two-layer highway network.

**Encoding layers.** The output from the embedding layer for the question and context are fed into a set of recurrent layers. Recurrent layers offer the benefit of explicitly modeling sequential structure and thus encode a complete sequence of words into a fixed-size vector. Formally, the output $o_j$ of a recurrent layer when processing the $j$-th term is calculated from the $j$-th hidden state $h_j$ via $o_j = f(h_j)$. The hidden state is, in turn, computed from the current input $x_j$ and the previous hidden state $h_{j-1}$ via $h_j = g(h_{j-1}, x_j)$, thereby introducing a recurrent relationship. The actual implementation of $f(\ldots)$ and $g(\ldots)$ depends on the architectural choice: BiDAF and DrQA utilize long short-term memories, while R-Net instead draws upon gated recurrent units, which are computationally cheaper but also offer less flexibility. All

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Fig. 2. Schematic architecture of the different neural network architectures (i.e. DrQA, BiDAF, R-Net) used in the answer extraction module.
models further extend these networks via a bidirectional structure in which two recurrent networks process the input from either direction simultaneously.

**Question-context fusion.** Both questions and context have been previously been processed separately and these are now combined in a single mathematical representation. To facilitate this, neural networks commonly employ an attention mechanism [Bahdanau et al. 2015], which introduces an additional set of trainable parameters in order to better discriminate among individual text segments according to their relevance in the given context. As an example, the interrogative pronoun "who" in a question suggests that the name of a person or entity is sought and, as a result, the network should focus more attention on named entities. Mathematically, this is achieved by an additional dot product between the embedding of "who" and the words from the context, which is further parametrized through a softmax layer. The different networks vary in in how they implement the attention mechanisms. The DrQA draws upon a fairly simple attention mechanism, while both BiDAF and R-Net utilize a combination of multiple attention mechanisms.

**Prediction layer.** The final prediction is responsible for determining the beginning and ending position of the answer within the context. DrQA utilizes two independent classifiers for making the predictions. This has the potential disadvantage that the ending position does not necessarily come after the starting position. This is addressed by both BiDAF and R-Net, where the prediction of the end position is conditioned on the predicted beginning. Here the BiDAF network simply combines the outputs of the previous layers in order to make the predictions, while R-Net implements an additional pointer network.

### 3.3 Domain Customization

The performance of question-answering techniques is commonly tested in highly artificial settings, i.e. consisting of datasets that rarely match the characteristics of business settings. Based on our practical experience, we identified two important levers that help in tailoring Q&A systems to specific applications, namely, (i) an additional manual filter mechanism to restrict the scope of the desired answer and (ii) transfer learning as a tool for re-using knowledge from related, yet different, tasks. These mechanisms target different components of a Q&A system: the selection mechanism affects the behavior of the IR module, while transfer learning addresses the answer extraction.

In most applications, Q&A systems cover a wide area of knowledge, while a question addresses only a certain sub-area of it. For instance, questions in a business context might target a specific firm department (e.g. marketing, human resources) or a certain industry branch. Similarly, Q&A systems in medicine could be additionally augmented by anatomical factors or by other health-specific categorizations such as disease codes. In actual software applications, this selection criterion could be implemented as a simple drop-down list and is methodologically realized by a simple filter operation on the dataset. In our later evaluation, the system retrieves information from financial news concerning specific firm developments and we thus experiment with a selection mechanism that filters by firm name. As a result, this helps in greatly narrowing the search space; however, more interestingly, it yields an overproportionate improvement in performance.

Due to the complexity of contemporary deep neural networks, one commonly requires extensive datasets with thousands of samples for training all their parameters in order to prevent overfitting and obtain a satisfactory performance [Rajpurkar et al. 2016]. However, such large-scale datasets are extremely costly to acquire, especially for applications that require expert knowledge. As a remedy, we propose the use of transfer learning as an efficient alternative to domain-specific customizations of the answer extraction module inside Q&A systems. This method allows the network to better learn the general functionality of question answering and thus requires a significantly smaller dataset for adapting to domain-specific characteristics. More precisely, we draw upon a different dataset that
contains general, open-domain question-answer pairs. Such datasets for transfer learning can easily consist of 100,000 or more samples, which are merged with a considerably smaller set of a few hundred question-answer pairs from a domain-specific background. The deep neural network is then trained on this combined dataset with additional oversampling of domain-specific questions by a factor of three.

We later also run a sensitivity analysis with an alternative strategy to transfer learning as a comparison, whereby the network is consecutively trained: first with open-domain dataset and afterwards fine-tuned using the domain-specific samples. This approach oftentimes represents the naïve technique for transfer learning [Pan & Yang 2010], even though entails an inherent disadvantage as the results are highly dependent on the hyperparameters, which need to be carefully tuned in each stage and thus introduce considerably more instability during training.

3.4 Dataset

We demonstrate our proposed methods for domain customization using an actual application of question answering from a business context, i.e. where a Q&A system answers question regarding firm developments based on financial news. We specifically decided upon this use case due to the fact that financial news presents an important source of information for decision-making in financial markets [Granados et al. 2010]. Hence, this use case is of direct importance to a host of practitioners, including media and investors. Moreover, this setting presents a challenging undertaking, as financial news is known for its complex language and highly domain-specific terminology.

Our dataset consists of financial news items (i.e. so-called ad hoc announcements) that were published by firms in English as part of regulatory reporting rules and were then disseminated through standardized channels. We proceeded with this dataset as follows: A subset of these news items was annotated and then split randomly into a training set (60% of the samples) as well as a test set (40%). As a result, we yield 63 documents with a total of 393 question-answer pairs for training. The test set consists of another 63 documents with 257 question-answer pairs, as well as 13,272 financial news items without annotations. This reflects the common nature of Q&A systems that have to extract the relevant information oftentimes from thousands of different documents. Hence, this is necessary in order to obtain a realistic performance testbed for the overall system in which the information retrieval module is tested. In other words, the information retrieval module has a probability of only $1/13,335 \approx 0.7 \times 10^{-4}$ of returning the right document when choosing a news item at random. Table 1 provides an illustrative set of question-answer pairs from our dataset.

| Document                                                                 | Question                                      | Answer          |
|--------------------------------------------------------------------------|-----------------------------------------------|-----------------|
| … Dialog Semiconductor PLC (Xetra: DLG), a provider of highly integrated power management, AC/DC power conversion, solid state lighting and Bluetooth(R) Smart wireless technology, today reports Q4 2015 IFRS revenue of $397 million, at the upper end of the guidance range announced on 15 December 2015. … | What is the level of Q4 2015 IFRS revenue for Dialog Semiconductor PLC? | $397 million |
| … Dr. Stephan Rietiker, CEO of LifeWatch, stated: “his clearance represents a significant technological milestone for LifeWatch and strengthens our position as an innovational leader in digital health. Furthermore, it allows us to commence our cardiac monitoring service in Turkey with a patch product offering.” … | Where does LifeWatch plan to start the cardiac monitoring service? | Turkey |

Table 1. Two samples for question-answer pairs. The table shows the snippet of the news item, together with the location of the (shortest) ground-truth answer within it.

All documents were further subject to conventional preprocessing steps [Manning & Schütze 1999], namely, stopword removal and stemming. The former removes common words carrying no meaningful information, while the latter

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3The dataset has been made publicly available via: https://github.com/anonymized.
removes the inflectional form of words and reduces them to their word-stem. For instance, the words *fished, fishing* and *fisher* would all be reduced to their common stem *fish*.

Our application presents a variety of possibilities for implementing an additional filter mechanism, such as making selections by industry sector or firm. However, together with practitioners, we determined that questions always relate to specific news articles and thus necessarily involve a firm name. For instance, the question *“What is the adjusted net sales growth at actual exchange rates in 2017?”* cannot be uniquely answered without defining a company. Hence, we implemented an additional filter mechanism by firm name for our experiments. This also provides direct benefits in practical settings as it saves the user from having to type such identifiers and thus improves the overall ease-of-use.

We further draw upon a second dataset during transfer learning, the prevalent Stanford Question and Answer (SQuAD) dataset [Rajpurkar et al. 2016]. This dataset is common in Q&A systems for general-purpose knowledge and is further known for its extensive size, as it contains a total of 107,785 question-answer pairs. Hence, when merging the SQuAD and our domain-specific dataset, the latter only amounts to a small fraction of 0.6% of all samples. This explains the need for oversampling, such that the neural network is trained with the domain-specific question-answer pairs to a sufficient extent.

### 4 RESULTS

This section compares both strategies for customizing question-answering systems to business applications. Since each approach addresses a different module within the Q&A system, we later evaluate the sensitivity of interactions with the corresponding component in an isolated manner.

#### 4.1 Domain Customization

We now evaluate the different approaches to domain customization. The overall performance is measured by the fraction of *exact matches* (EM) with the ground-truth answer. Answers in the context of Q&A are only counted as an exact match when the extracted candidate represents the shortest possible sub-span with the correct answer. Even though this is identical to accuracy, we avoid this term here in order to prevent misleading interpretations and emphasize the characteristics of the shortest sub-span. In addition, we measure the relative overlap between the candidate output and the shortest answer span by reporting the proportional match between both bag-of-words representations, yielding a macro-averaged F1-score for comparison. As a specific caveat, we follow common conventions and compute the metrics by ignoring punctuations and articles.

Table 2 reports the numerical results. For all methodological strategies, we first list the performance without domain customization as a benchmark and, subsequently, incorporate the different approaches to domain customization. Without domain customization, the Q&A system can (at best) answer one in 7.6 questions correctly, while the performance increases to one in 3.7 with the use of the additional selection mechanism.

All algorithms incorporating deep learning clearly outperform the baselines from the literature. For instance, the DrQA system yields an exact match in one out of 3.3 cases. Here we note that two DrQA systems are compared: namely, one following the reference implementation [Chen et al. 2017] – whereby five documents are returned by the information retrieval module and the extracted answer is scored for each – and, for reasons of comparability, one approach that is based on the best-fit document, analogous to the other neural-network-based systems.

We observe considerable performance improvements as a result of applying transfer learning. It can alone increase the ratio of exact matches to one out of 2.4 questions and, together with the selection mechanism, it even achieves a score of one out of 2.2. This increases the performance of the best-scoring benchmark without domain customization by
3.9 and 19.8, respectively. The gains yielded by the selection mechanism come naturally, but we observe that a limited, domain-specific training set can also boost the performance considerably. Notably, neither baseline can be further improved with transfer learning, as this technique is not applicable (e.g., the sliding window approach lacks trainable parameters).

The DrQA system that considers the top-five documents yields the superior performance in the first two experiments: the plain case and the one utilizing transfer learning. However, the inclusion of the additional selection mechanism alters the picture, as it essentially eliminates the benefits of returning more than one document in the information retrieval module. Apparently, extracting the answer from multiple documents is useful in settings where the information retrieval module is less accurate, whereas in settings with precise information retrieval modules, the additionally returned documents introduce unwanted noise and prove counterproductive. Hence, we specifically study the implications with regard to the information retrieval module in the next section.

| Method                      | No domain customization | Transfer learning | Selector | Transfer learning + selector |
|-----------------------------|-------------------------|-------------------|----------|-----------------------------|
|                             | EM F1                   | EM F1             | EM F1    | EM F1                       |
| **Baseline systems**        |                         |                   |          |                             |
| Sliding window              | 5.4 7.1 n/a             | 11.7 15.9 n/a     | n/a n/a  |                             |
| Logistic regression         | 13.2 21.0 n/a           | 27.2 39.5 n/a     | n/a n/a  |                             |
| **Deep learning systems**   |                         |                   |          |                             |
| DrQA (best-fit document)    | 24.9 34.9 (17.3%) (13.5%) | 44.4 57.6 (65.0%) (104.8%) | 51.0 63.7 (82.5%) |                             |
| DrQA (reference implementation) | 30.0 41.6 (13.0%) (9.1%) | 40.1 52.4 (33.7%) (26.0%) | 47.1 59.3 (57.0%) (42.5%) |                             |
| R-Net                       | 18.7 26.4 (18.7%) (8.0%) | 33.9 48.4 (81.3%) (83.3%) | 38.1 50.7 (103.7%) (92.0%) |                             |
| BiDAF                        | 26.5 33.0 (7.6%) (2.4%) | 46.3 58.7 (75.4%) (77.9%) | 49.8 60.6 (88.6%) (83.6%) |                             |

Table 2. Performance comparison of different strategies for domain customization. Here the plain system without domain customization is benchmarked against transfer learning and the additional selection mechanism by firm name. Additionally, relative performance improvements over the baseline without domain customization are reported for each implementation with additional highlighting in bold for the best-performing system in each experimental setup. Notably, transfer learning is not applicable to the baseline systems.

4.2 Information Retrieval Module

This section examines the performance of the information retrieval module isolated from the rest of the Q&A pipeline. This allows us to study the interactions between the additional selection mechanism and the precision of the document retrieval. Furthermore, we run a sensitivity analysis in order to investigate the effects of using bigrams over unigrams.

The information retrieval module is evaluated in terms of recall@k. This metric measures the ratio of how often the relevant document $d_q$ is within the top-$k$ ranked documents. Potentially more than one document can include the...
desired answer $a$ and we thus treat all documents with $a \in d$ as a potential match. As a comparison, the information retrieval module is evaluated against a random mechanism that returns $k$ random documents.

Table 3 shows the numerical outcomes. In the plain case without domain customization, our dataset includes a total of 13,335 entries, due to which the recall of the baseline amounts to almost zero (i.e. $1/13,335 \approx 0.7 \times 10^{-4}$). The selector reduces the number of potential documents after filtering for the firm name, yielding a probability of 0.46, on average, of choosing the right document for a given query. Exchanging unigrams for bigrams results in only marginal performance changes. However, we observe a considerable jump when utilizing the pre-selection technique. Here the recall@1 improves from 0.48 to 0.88; i.e. an increase of 0.4. The increase appears especially when returning one document opposed to five, since the corresponding relative improvement amounts to a 83.3 % in terms recall@1 and only 45.5 % for the recall@5.

The experiments partially explain the performance gains of this domain customization technique in the overall system. The result also goes hand in hand with our finding that an information retrieval module with low recall benefits especially from taking multiple documents into account. In other words, extracting the answer from multiple documents is useful in settings where the information retrieval module is less precise. Yet the opposite pattern emerges for an IR module with high recall, as returning multiple documents augments the noise in answer extraction and can ultimately lower the overall performance. Due to the additional selection criterion, the information retrieval module becomes very accurate and, as a result, the performance of the answer extraction module becomes especially critical, since it usually represents the most sensitive part of the Q&A pipeline. The following section thus evaluates the sensitivity of the answer extraction component.

| Approach                        | Recall@1 | Recall@3 | Recall@5 |
|--------------------------------|----------|----------|----------|
| **IR module without domain customization** |          |          |          |
| Baseline: random choice         | 0.00$\dagger$ | 0.00$\dagger$ | 0.00$\dagger$ |
| Unigrams                        | 0.35     | 0.47     | 0.53     |
| Bigrams                         | **0.48** | **0.62** | **0.66** |
| **IR module without firm selector** |          |          |          |
| Baseline: random choice         | 0.46     | 0.76     | 0.88     |
| Unigrams                        | 0.84     | 0.95     | 0.96     |
| Bigrams                         | **0.88** | **0.96** | **0.96** |

$\dagger$: $1/13,335 \approx 0.7 \times 10^{-4}$

Table 3. Comparison of how different variants of information retrieval affect the performance of this module. Here the average recall is measured when returning the top-$k$ documents (the best score for each choice of $k$ is highlighted in bold). As we can see, the performance changes only slightly when exchanging bigrams for unigrams, yet the selection mechanism corresponds to notable improvements.

### 4.3 Answer Extraction Module

This section studies the sensitivity of implementing domain customization within the answer extraction module. Accordingly, we specifically evaluate how transfer learning increases the accuracy of answer extraction and we compute the number of matches, given that the correct document is supplied, in order to assess the performance of this module.
in an isolated manner. That is, we specifically measure the performance in terms of locating the answer $a$ to a question $q$ in a given document $d_q$.

The results of our experiments are shown in Table 4. Here we distinguish three approaches: (i) the baseline without transfer learning for comparison, (ii) the naïve approach to transfer learning from the literature [Pan & Yang 2010] whereby the networks are first trained based on the open-domain dataset before being subsequently fine-tuned to the domain-specific application and (iii) our approach whereby we create a fused dataset such that the network is simultaneously trained on both question-answer pairs (but where the domain-specific corpus is oversampled in order to better handle the imbalances). The results reveal considerable performance increases across all neural network architectures. The relative improvements can reach up to 17.0 %.

The results clearly demonstrate that the fused approach (iii), based on a fused dataset, consistently yields the superior performance. Its relative performance improvements range between 3.2 and 13.0 percentage points higher than for strategy (ii). An explanation is that fine-tuning network parameters on a domain-specific dataset of such small size is a challenging undertaking, as one must manually calibrate the number of epochs, batch size and learning rate in order to avoid overfitting. For example, a batch size of 64 yields an entire training epoch on our dataset that consists of only six training steps. This in turn makes hyperparameter selection highly fragile. In contrast, training on the fused data proves to be substantially more robust and, in addition, requires less knowledge of training the network parameters.

| Neural network | Baseline: no transfer learning | Transfer learning: two-staged tuning | Transfer learning: fused dataset |
|----------------|--------------------------------|-------------------------------------|-------------------------------|
|                | EM F1                          | EM F1                              | EM F1                         |
| DrQA           | 51.4 66.3                      | 53.2 67.3                           | 59.9 72.2                     |
|                | (3.5 %) (1.5 %)                | (16.5 %) (8.9 %)                   | (17.0 %) (9.6 %)              |
| R-Net          | 38.9 55.2                      | 41.2 56.5                           | 45.5 60.5                     |
|                | (5.9 %) (2.4 %)                | (17.0 %) (9.6 %)                   | (17.0 %) (9.6 %)              |
| BiDAF          | 53.3 67.4                      | 55.6 68.4                           | 57.6 70.0                     |
|                | (4.3 %) (1.4 %)                | (8.1 %) (3.9 %)                    | (8.1 %) (3.9 %)               |

Table 4. Sensitivity analysis comparing different methods for transfer learning. Here it is solely the accuracy of the answer extraction module that is evaluated; that is, the correct document is given and only the location of the correct answer is unknown. Accordingly, the performance achieves slightly higher values in comparison to earlier assessments of the overall system. Transfer learning based on a fused dataset yields a consistently superior performance as compared to the naïve two-stage approach. The performance of each network architecture relative to its baseline is reported and the best-performing approach is highlighted in bold.

5 DISCUSSION

5.1 Domain customization

Hitherto, a key barrier to the widespread use of Q&A systems has been the inadequate accuracy of such systems. Challenges arise especially when practical applications, such as those in the domain of finance, entail complex language with highly special terminology. This requires an efficient strategy for customizing Q&A systems to domain-specific characteristics. Our paper proposes and evaluates two such levers: direct filter mechanisms for choosing sub-domains and transfer learning. Both entail fairly small upfront costs and generalize across all domains and application areas, thereby ensuring straightforward implementation in practice.
Our results demonstrate that domain customization greatly improves the performance of question-answering systems. The mechanism for sub-domain filtering increases the number of exact matches with the shortest correct answer by up to 81.3%, while transfer learning yields gains of up to 18.7%. Here the improvements from the additional filter mechanism are fairly intuitive, whereas the use of transfer learning presents an intriguing, cost-efficient path to domain customization. For this reason, the Q&A system performs an inductive transfer of knowledge from a different, unrelated dataset to the domain-specific application, for which one can utilize existing datasets that sometimes include more than 100,000 entries and are publicly available.

Transfer learning entails further managerially-relevant benefits, as the manual process of labeling thousands of question-answer pairs for each domain-specific application is rendered unnecessary. Instead, only a few hundred samples are sufficient for training the deep neural networks and achieving significant performance improvements. In our case, the system requires a small dataset of as few as 400 annotated question-answer pairs. This is especially beneficial in business settings where annotations demand extensive prior knowledge (such as in medicine or law) since here the necessary input from domain experts is greatly reduced.

5.2 Managerial implications

Question answering presents an effective technique for retrieving knowledge from information systems. Its capabilities greatly aid individuals, firms and organizations burdened with ever-increasing volumes of data [Chen et al. 2012] and in need of access to the right information at the right time in order to base their decision-making and create value. To this end, question answering promises to function as a convenient interface for information systems, as it replaces the manual filtering involved in traditional search processes by directly displaying the desired information.

Question answering fosters innovation in the realm of information systems and promises, in particular, to advance modern knowledge management systems. In this domain, this technique can generate value in applications where its use has been largely overlooked. For example, audits control a firm’s financial documents according to predefined procedures, for which frequent manual look-ups of information could be replaced by automated question answering. Other applications include systems for customer relationship management or enterprise resource planning, in which question-answering technology controlled via voice command could simplify interactions. One could analogously adapt this to groupware software or personal email clients, similar to the functionality that is nowadays built into smartphones in the form of, e.g., Siri, Cortana or Google Now. This technology might also help academics who wish to analyze linguistic content [e.g. Chau & Xu 2012].

5.3 Implications for research

Our experiments reveal another source of performance improvements beyond domain customization: replacing the known answer extraction modules with transfer learning and, instead, tapping advanced neural network architectures into the Q&A system. This is interesting in light of the fact that deep neural networks have fostered innovations in various areas of natural language processing, and yet publications pertaining to question answering are limited to a few exceptions [Chen et al. 2017; Wang et al. 2018, 2017a]. Additional advances in the field of deep learning are likely to present a path towards further bolstering the accuracy of the system.

Future research could evolve Q&A systems in several directions. First, considerable effort will be needed to overcome the current approach whereby answers can only be sub-spans of the original documents and, instead, devise a method in which the system re-formulates the answer by combining information across different documents. Second, Q&A systems should be extended to better handle semi-structured information such as tables or linked data, since these are
common in today’s information systems. Third, practical implementations could benefit from ensemble learning [c.f. Seo et al. 2017; Wang et al. 2017b] and by relaxing the assumption of deciding upon the most promising document \(d \in D\) as part of the information retrieval module. Instead, the top-\(n\) documents could be returned and the final choice could be made after extracting the candidate answer from each, ideally in an end-to-end trainable network.

6 CONCLUSION

Users, and especially corporations, demand efficient access to the knowledge stored in their information systems in order to fully inform their decision-making. Such retrieval of information can be achieved through question-answering functionality. This can overcome limitations inherent to the traditional keyword-based search. More specifically, Q&A systems are known for their ease of use, since they enable users to interact conveniently in natural language. This also increases the acceptance rates of information systems in general and accelerates the overall search process. Despite these obvious advantages, inefficient domain customization represents a major barrier to Q&A usage in real-world applications, a problem for which this paper presents a powerful remedy.

This work contributes to the domain customization of Q&A systems as follows: We first demonstrate that practical use cases can benefit from simple filter mechanisms by sub-domains. Furthermore, we propose the use of transfer learning in order to reduce the need for pre-labeled datasets. Only relatively small sets of question-answer pairs are needed to fine-tune the neural networks, whereas the majority of the learning process occurs through an inductive transfer of knowledge. Altogether, this circumvents the needs for hand-labeling thousands of question-answer pairs as part of tailoring question answering to specific domains; instead, the proposed methodology requires comparatively little effort and thus allows even small businesses to take advantage of deep learning.

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