Abstract

Question answering systems should help users to access knowledge on a broad range of topics and to answer a wide array of different questions. Most systems fall short of this expectation as they are only specialized in one particular setting, e.g., answering factual questions with Wikipedia data. To overcome this limitation, we propose composing multiple QA agents within a meta-QA system. We argue that there exist a wide range of specialized QA agents in literature. Thus, we address the central research question of how to effectively and efficiently identify suitable QA agents for any given question. We study both supervised and unsupervised approaches to address this challenge, showing that TWEAC—Transformer with Extendable Agent Classifiers—achieves the best performance overall with 94% accuracy. We provide extensive insights on the scalability of TWEAC, demonstrating that it scales robustly to over 100 QA agents with each providing just 1000 examples of questions they can answer. Our code and data is available.

1 Introduction

Existing question answering systems are limited in the types of answers they can provide and in the data sources they can access. For instance, QA systems that rely on a powerful reading comprehension model (e.g., Yang et al., 2019; Chen et al., 2017) cannot answer questions that require access over structured data, e.g., for providing information about the weather (Will it rain today at 9 am in New York?) or public transportation (When is the next train departing from London to Liverpool?). Even though recent work has studied how to better generalize QA models across different domains or question types (Rücklé et al., 2020; Guo et al., 2020; Yang et al., 2020; Talmor and Berant, 2019), they investigate only a small fraction of the broad questions that humans may ask (see Table 1).

One approach for answering a much broader range of questions is a meta-QA system that composes various QA agents, i.e., specialized QA subsystems. In this work, we address the central research question that arises when developing such a system: how can we efficiently and accurately identify one or multiple QA agents to which we can route the given question (see Figure 1)?

This is conceptually similar to skill selection in dialog systems (Li et al., 2019b; Kim et al., 2018; Burtsev et al., 2018), with two central differences: (1) Our setting focuses exclusively on QA and avoids dealing with personalization and dialog history; (2) We are not limited in selecting one skill to address the user’s intention, but can invoke multiple QA agents in parallel—e.g., to return multiple answers or to perform consistency checks.

To the best of our knowledge, such an approach has not been studied before. We, therefore, lay the foundational groundwork for meta-QA systems and focus on the identification of suitable QA agents.

Importantly, we treat the QA agents as black boxes without further knowledge about their internal workings. This is advantageous because it
allows us to study the QA agent selection without external effects from the QA models themselves—e.g., whether they provide a correct answer. We thereby identify the following four challenges for the QA agent selection:

1. **Heterogeneous scopes and tasks:** We deal with imbalanced data, various types of questions, etc.
2. **Extensibility:** Adding QA agents seamlessly within minutes is crucial to make them available to the meta-QA system as quickly as possible.
3. **Scalability:** We should be able to handle over one hundred QA agents to cover a broad range of question types, data source, and topics.
4. **Small data:** Relevant QA agents should be identified even if they provide only a few examples of questions that they can answer.

To address this, we (1) create a realistic scenario based on 10 well-known QA tasks, and (2) construct two substantially larger datasets consisting of questions from 171 subreddits and 200 StackExchange forums. In both scenarios, a model receives a question and determines in which data set this question is likely to be observed—thus effectively determining the most appropriate QA agent. While our first scenario is realistic because it covers a wide range of question types that a QA system might receive, our second scenario addresses scalability with over a hundred different agents.

We study two kinds of models that scale well to a large number of QA agents. (1) similarity-based models using sentence embeddings and BM25 (Robertson and Zaragoza, 2009), finding that they achieve a high precision without additional fine-tuning; (2) Transformer with Extendable Agent Classifiers (TWEAC)—a highly scalable transformer model (Vaswani et al., 2017) that is extensible with hundreds of agents without full model re-training. Our results show that TWEAC is the most effective overall and achieves the best performances in both experimental settings.

We find that our models are very sample efficient—they require only one thousand examples for each QA agent at most to achieve up to 94% accuracy for identifying the correct one. Thus, they can be applied to many realistic scenarios in which we do not have large amounts of training data. Our models can also scale to many agents and still correctly identify the relevant agent.

We show that our proposed meta-QA system is feasible in realistic and large-scale scenarios even with extending QA agent ensembles and limited data. This opens up an alternative approach to QA systems whereby we can use multiple QA agents specialized on different questions instead of training a single model to handle all possible questions.

## 2 Related Work

Most of current QA systems are specific to an individual type of QA, e.g., community QA (Rücklé and Gurevych, 2017; Romeo et al., 2018), knowledge-base QA (Sorokin and Gurevych, 2018), or extractive open-domain QA (Yang et al., 2019). They implement very narrow QA agents and are not applicable across many different scenarios. More recently, research has expanded the scope to multi-domain approaches that can also be applied in zero-shot transfer scenarios (Talmor and Berant, 2019; Guo et al., 2020; Rücklé et al., 2020). Further, some approaches fuse different input sources such as text and knowledge bases (Sun et al., 2018, 2019; Xu et al., 2016). Singh et al. (2018) propose an adaptable pipeline approach where sub-components in the QA pipeline such as Named Entity Recognition can be selected to best suit the question. However, none of them address combining fundamentally different QA agents into one extensible system and all are limited to one particular kind of QA such as extracting answer spans from documents.

Consolidating different QA agents into one system is conceptually similar to skill systems in chatbots, where utterances can invoke one of many specialized skills. Skill systems are, for instance, part of modern chatbot frameworks, e.g., Deep Pavlov (Burstein et al., 2018) and ParlAI (Miller et al., 2017). An important research challenge in those scenarios is to better deal with a large and increasing number of skills in combination with user-specific preferences, as it is, for instance, the case in Amazon Alexa (Kim et al., 2018; Li et al., 2019a). They also focus on extensibility in their models but their LSTM models require training with hundreds of skills and millions of examples before it can be extended. Our methods require only hundreds or thousands of available examples.

Identifying QA agents is also related to intent classification (Liu and Lane, 2016; Kato et al., 2017; Gangadharaiah and Narayanaswamy, 2019; Qin et al., 2019) and question-type classification (Chernov et al., 2015; Komninos and Manandhar, 2016). These tasks, however, rely on fixed question and intent taxonomies, which limits the exten-
sibility of the developed approaches in practical scenarios.

Identifying QA agents capable of answering a question is related to human expert identification tasks such as CQA Expert Routing (Mumtaz et al., 2019; Li et al., 2019b) or Reviewer-Paper Matching (Zhao et al., 2018; Anjum et al., 2019; Duan et al., 2019). They differ from our agent identification as (1) they do not train models for specific experts but instead usually learn a shared embedding space for experts and questions, and (2) human expertise is modeled around the topics the humans are proficient in while our QA agents also differ in the kind of questions asked and not just the topic.

3 QA Agent Identification

Our goal is to retrieve the QA agents that can—most likely—answer a given question. In contrast to intent classification (e.g., Qin et al., 2019) where there is only one correct intent for any given query, we formulate QA agent identification as a ranking task. This is arguably a more realistic approach in our case because one question can potentially be answered by multiple agents.

3.1 Task Definition

Let \( A = \{A_1, A_2, \ldots, A_N\} \) be a set of \( N \) different QA agents and let \( q \) be a user question. Our goal is to rank the agents in \( A \) with respect to their (anticipated) ability to answer the question \( q \).

For each QA agent \( A_i \), we obtain a set \( E_i = \{e_1, \ldots, e_{n_i}\} \) of example questions that this agent can answer. We use those examples to train the supervised QA agent selection models.

3.2 Similarity-based Models

Our central approach is to adapt the k-nearest neighbor algorithm to rank agents in relation to a question \( q \). Given a function \( s(q, e) \) that measures the similarity between \( q \) and an example \( e \) from the example question set of an agent, we use \( s \) to retrieve the top-k most similar examples \( e_1, \ldots, e_k \). Using the examples, we score each agent with

\[
S(A_i) = \frac{1}{|E_i|} \sum_{j=1}^{k} I_{E_i}(e_j) s(q, e_j)
\]  

where \( I_{E_i}(e_j) \) is the indicator function indicating if the example \( e_j \) is in the set of example questions \( E_i \).

To address different example set sizes, we normalize by dividing with the example set size \(|E_i|\) of the respective agent.

We evaluate two similarity functions for \( s \): BM25 (Robertson and Zaragoza, 2009) and the dot product between sentence embeddings from the Universal Sentence Encoder QA (USE-QA) model (Yang et al., 2020), which was trained on a large question-answer dataset. We found empirically that \( k = 50 \) works well regardless of the number of agents.

Extending the similarity-based methods with new agents is efficiently done by adding the example questions from the new agent to the index. However, the approach might lack knowledge about the idiosyncrasies of particular QA domains. Next, we therefore also study a supervised transformer-based approach.

3.3 Transformer with Extendable Agent Classifiers (TWEAC)

TWEAC consists of a single transformer-based model with a classification head for each agent (see Figure 2), which decides whether an agent is capable of answering a question. We experiment with ALBERT (Lan et al., 2020) and RoBERTa (Liu et al., 2019).

Each classification head consists of two fully connected layers: The first layer has a dimensionality of 256 and uses a GELU activation (Hendrycks and Gimpel, 2016). The second layer outputs a scalar (with sigmoid activation). Each head, thus, represents the independent probability of whether one agent can answer the given question. We can then rank the agents by their probabilities. We implement the classification heads using two convolution layers with grouped convolutions for parallel execution which gives a sub-linear increase in run-time with respect to the number of classification heads, and it is computationally suitable for
classifying thousands of agents.\(^3\)

When adding a new agent to the model, we only introduce a new classification head. Afterward, the entire model is fine-tuned with both the training examples of the new agent and examples from previously added agents. Training with all available data can be infeasible if the model should be ready within minutes after an agent was added. We therefore also experiment with a sampling strategy that only uses a fraction of all data in §6.

We train the model by minimizing the binary cross-entropy (BCE) for each head. Each training example is considered a positive example for the correct agent and as a negative example for all other agents. Given the output of the head \(h_i\) for agent \(A_i\) and the label \(y = (y_1, \ldots, y_N)\) as a one-hot encoding of the correct agent, the loss for each head is defined as:

\[
L_i = -[w_i y_i \log(h_i) + (1 - y_i) \log(1 - h_i)]
\]  

(2)

Weighting of positive examples according to \(w_i = (\sum_{j \neq i} |E_j|)/|E_i|\) is necessary to balance the signals from positive and negative examples.

### 4 Data and Evaluation

For the evaluation of our models, we simulate agents through different datasets without explicitly training a QA agent for the questions. This way, we can focus on QA agent identification in an isolated setting without the influence of errors from real QA agents. We construct two setups for evaluation: QA-Tasks and Many-Agents.

#### 4.1 QA Tasks

We model a realistic QA scenario with distinct types of questions and minimal overlap between the agents by using questions from different QA datasets from the literature. We construct the dataset QA-Tasks with 10 agents for different QA tasks.

**Community QA (CQA)** is a variant of retrieval-based QA and re-uses the large quantities of questions and answers that have been discussed in question-answering forums (Nakov et al., 2017; Tay et al., 2017; Rücklé et al., 2019b,a). We use question titles from multiple StackExchange forums\(^4\) to cover a range of topics. StackExchange groups their forums in five categories and we select two forums from each category\(^5\). We do not filter the titles so examples can also include just keywords or sentences that are not proper questions.

**Knowledge Base QA (KBQA)** answers factoid questions using a knowledge base (Cui et al., 2017). We use the questions from QALD-7 (Usbeck et al., 2017) and WebQSP (Yih et al., 2016) as examples.

**Span-based Reading Comprehension (Span RC)** extracts the answer to a question from a corpus of text. The examples for this agent come from SQuAD (Rajpurkar et al., 2016)

**Multihop RC** differs from Span RC as the agent must now perform a multi-step search over multiple documents. We use HotPotQA (Yang et al., 2018) as a source for the questions.

**Non-factoid QA** requires descriptions or explanations as answers in contrast to factoid questions. We use WikiPassageQA (Cohen et al., 2018) as the dataset. Different from CQA, which likewise includes non-factoid questions, WikiPassageQA uses Wikipedia data as answers and the questions have been crowd-sourced.

**Reasoning RC** covers a range of questions that require higher reasoning like arithmetic or comparisons as proposed by Dua et al. (2019). We use their DROP dataset for example questions.

**Boolean QA** is an RC task with questions that have a yes/no answer as proposed by Clark et al.

\(^3\)Inference time increases by a factor of 2 when scaling from 10 to 1000 heads and by a factor of 6 when scaling to 5000 heads.

\(^4\)https://archive.org/download/stackexchange

\(^5\)Categories are: Technology, Culture/Recreation, Life/Arts, Science, and Professional (https://stackexchange.com/sites). We include StackOverflow, Superuser, Gaming, English, Stats, Math, Cooking, Photo, Writers, and Workplace.

| QA Agent       | Example Question                                      |
|----------------|-------------------------------------------------------|
| CQA            | Best browser for web application                      |
| KBQA           | Who is the mayor of Tel Aviv                          |
| Span RC        | Who can enforce European Union law                    |
| Multihop RC    | When was the writer of Seesaw born                    |
| Non-factoid QA | How did Beatlemania develop                           |
| Reasoning RC   | Who was first, Edward II or Richard I                  |
| Boolean QA     | Is a yard the same as a meter?                        |
| Claim Validation | Obama’s birth certificate is a forgery               |
| Weather Report | What will the weather be in Tontitown                 |
| Movie Screening| Find the films at Century Theatres                     |

Table 1: Examples from the 10 QA agents that correspond to 10 common QA tasks in the QA-Tasks dataset.
We use their BoolQ for the agent. The questions are based on Google queries which have a Wikipedia passage that answers the question.

Claim Validation fact-checks if a claim is supported by evidence. We use the Snopes Corpus created by Hanselowski et al. (2019). The difference to Boolean QA is that the claims and the evidence are from Snopes who include potentially unreliable sources including false news sites.

Weather Report & Movie Screening are two agents that we use as examples for highly specialized questions which can be seen as skills or intents in conversational agents. Both agents use examples from the NLU Benchmark by Coucke et al. (2018) for the intents GetWeather and Search-ScreeningEvent respectively.

Dataset Splits: We use the splits of the published datasets. If the test set is unavailable, we use the development split as the test set and remove the last 25% of the training data to obtain a new dev set. We also obtain a dev set for QALD-7 and WebQSP the same way. For the StackExchange data, each forum is split into train, dev, and test set, such that each split contains all 10 forums.

4.2 Large-Scale QA Agent Identification

A meta-QA system as we propose can have a large number of agents, e.g., in a public system where developers can publish their agents. Some might be general QA agents, while others are highly specialized agents able to answer questions for specific domains or tasks. We simulate such a setup using 171 forums from StackExchange and 200 randomly selected subreddits from reddit. We consider all post titles as questions to obtain a sufficient number of examples for each agent. We term this setup Many-Agents.

It is important to note that this setup is artificial in that we separate agents primarily by topics and less by the types of questions. There is also a higher overlap between questions of different forums: while each StackExchange forum and subreddit is dedicated to a specific topic, there might be a certain overlap between related topics, e.g., English and English Language Learners in StackExchange. Nevertheless, we argue that this approach allows us to investigate a larger number of agents and how our models can scale to such numbers than would be possible when relying on QA research datasets as in §4.1.

5 Experiments

We evaluate the models with respect to their (1) support of heterogeneous scopes and tasks, (2) performance with little training data, and (3) scalability. Our two setups from §4 are created with (1) in mind and our experiments that we introduce in what follows consider (2) and (3) as well. Later in §6, we investigate how to efficiently extend TWEAC with new agents. In addition, we provide a comparison of inference speed between our models for the agent selection in Appendix §A.1.

5.1 Experimental Setup

Models and Hyperparameters. For the similarity-based models, we empirically find that \( k = 50 \) works the best and use this in all experiments. As for similarity functions, we compare BM25 and USE-QA with the dot-product.

For the transformer based ranker (TWEAC), we use ALBERT base (denoted as TWEAC\(_{A-b}\)), ALBERT large (TWEAC\(_{A-l}\)) and RoBERTa large (TWEAC\(_{R-l}\)). We train all models for 10 epochs with a batch size of 32, a learning rate of 1e-4 (or 2e-5 for large transformers) with a linear warm-up during the first epoch. The hyperparameters were chosen after some preliminary training runs on QA-Tasks.

We report Accuracy@1 and mean reciprocal rank (MRR) as performance scores. We make the assumption that only the agent from the respective dataset from which we draw the test question is relevant, all other agents are irrelevant. This assumption is a result of our dataset construction.

Sample Efficiency. We test how many example questions are needed to achieve appropriate ranking results. We evaluate our models on QA-Tasks with 64 up to 4096 examples per agent. We note that five agents have less than 4000 examples which is accounted for in our weighting component (see Equation 1 and 2). TWEAC is trained with all 10 agents at the same time. We adjust the number of epochs accordingly to keep the number of update steps equal to 10 epochs with 1024 examples.

---

\(^6\)BoolQ, HotPotQA, DROP, SQuAD, NLU Benchmark

\(^7\)BigQuery (https://console.cloud.google.com/bigquery/) table fh-bigquery:reddit_posts

\(^8\)Claim Validation (3847), Non-factoid QA (3331), KBQA (2398), Weather Report & Movie Screening (226 each)
Scalability. We train models in Many-Agents with an increasing number of agents to evaluate the scalability of the different models. For both reddit and StackExchange, we train a model with 10, 50, 100 and 171 (StackExchange)/200 (reddit) agents. TWEAC is newly trained for each set of agents (using 1024 examples per agent).

5.2 Results

Sample Efficiency. Figure 3 shows the performance of methods in QA-Tasks as a function of the number of training examples per agent.\(^9\)

The TWEAC models achieve with 64 examples already over 80% accuracy and over 90% with a thousand examples. Similarity-based models perform noticeably worse—especially with very few examples—but reduce the gap to TWEAC with a larger number of examples. Starting at 1024, more examples have a diminishing return for TWEAC and might negatively impact the similarity-based models. Independent of how large we select the example sets for the agents, we observe the same performance ranks for the five evaluated systems with TWEAC\(_{R-l}\) performing best and BM25 performing worst.

Inspecting the performances of individual agents, we find that highly specialized agents such as Weather Report and Movie Screening perform very well (≥95% accuracy) with very few examples. QA Agents with a wider range of possible questions or topics like CQA or Span RC, on the other hand, are disproportionately worse with few examples. However, the need for more examples with such agents is often no problem in practice as they likely require more training data for the agent subsystem and, thus, have more examples available.

Scalability. We present the results of the large-scale experiments with Many-Agents in Figure 4 as a function of the number of agents.\(^10\) In contrast to the previous experiment, we now observe rank changes between our methods when increasing the number of agents. In particular, USE-QA achieves better results compared to TWEAC\(_{A-b}\) and TWEAC\(_{A-l}\), and with a smaller number of 10 agents it also outperforms TWEAC\(_{R-l}\) on the StackExchange dataset. A potential reason for the better performance of USE-QA with Many-Agents compared to QA-Tasks is that USE-QA has been trained on reddit and StackExchange data.

We observe similar performance drops across all models ranging from 20 to 30 points accuracy and MRR when increasing the agents from 10 to the maximum number. This is expected, as the task difficulty increases with a larger pool of agents. Further, as we analyze in Section 7, most mistakes stem from similar topics, e.g., the agent for the Math StackExchange ranked higher than the Statisti-

---

\(^9\)Precise numbers for these figures can be found in the respective tables in the appendix.

\(^10\)Detailed results are given in the appendix.
tics StackExchange agent for a statistics question. Even for a large pool of agents, we still achieve high Accuracy@1 results compared to a random baseline, and the correct agent is ranked on average at least second with all models (except BM25).

Summary. Our proposed models manage to identify the correct agents with high precision in a realistic setup with 10 QA tasks while also scaling well to hundreds of agents. They can achieve good performances even with as little as 64 training examples per agent. TWEAC—especially with large transformers—outperforms similarity-based models in most of our experiments.

6 Extending TWEAC

In a realistic setting, we may want to add new QA agents over time. Similarity-based models only need to index the new examples. Extending TWEAC is comparatively harder as it needs to be fine-tuned for the new agent. Re-training on all available data each time we add a new agent would be prohibitive and it would take hours until a new agent is eventually integrated into the system.

We consider a half-and-half sampling strategy that uses a constant number of examples regardless of the number of agents. It uses all 1024 examples from the extended agent but randomly selects $1024 / (|\text{agents}| - 1)$ examples from each of the other agents where $|\text{agents}|$ is the number of agents in the model for a total of approximately 2048 examples in total. Each epoch, a new set of examples is selected. We hypothesize that just a few examples from the previously added agents are necessary as (1) the heads were already trained with the examples in previous iterations and (2) the new head requires just a subset of the negative examples to distinguish them from its own examples.

The baseline no sampling uses all available examples for each agent when extending the model. With full training, we train a new model from scratch with all agents and do not extend a previously trained model.

Extending TWEAC Once. We extend the model from 9 to 10 agents in the QA-Tasks setup. We evaluate this with a leave-one-out approach: We train TWEAC with 9 of the agents and extend with the remaining one. We repeat this for each agent and report the average results. During extension, we train the entire model including the transformer and all classification heads. We compare against a model that was fine-tuned with examples from all 10 agents. We present the results in Table 2.

We see that extending with no sampling performs as well as the model trained directly with all 10 agents. The model trained with half-and-half sampling slightly drops in accuracy by 2 points.

Iterative Extension. We iteratively extending TWEAK one agent at a time with the Many-Agents datasets. We start with 10 or 50 agents and extend to 100.

We plot the accuracy as a function of the number of extended agents in Figure 5. After iterative extension from 10 to 100 agents, half-and-half sampling is 4 points better for reddit and on-par with StackExchange compared to no sampling. The gap between the two with the model starting at 50 agents is 2 points for both datasets. Half-and-half sampling can thus be used to train models with only a fraction of all examples without a decrease in performance compared to using all examples. However, models trained directly with all agents attain higher scores than iterative extension with half-and-half sampling. The gap between a model trained with all 100 agents and half-and-half starting at 10 agents is 7/4 points but it shrinks to 5/2 points when starting with 50 agents.

Summary. Out of the analyzed options, full training TWEAC from scratch yields the highest accuracy. However, the training time increases linearly with the number of QA agents. Using half-and-half sampling, we can rapidly extend the model with new QA agents. It has roughly a constant training time independent of the number of previously existent QA agents. The resulting slight drop in performance can be reduced by periodically full training a model with all agents.

| Strategy          | Accuracy | MRR   |
|-------------------|----------|-------|
| Full training     | 0.9096   | 0.9462|
| No sampling       | 0.9105   | 0.9467|
| Half-and-half      | 0.8860   | 0.9311|

Table 2: Average performance of extending a model from 9 to 10 agents from QA-Tasks with no sampling or half-and-half sampling compared to a model directly trained on all 10 agents (full training).

11 Exact numbers can be found in the tables in the appendix.
7 Analysis

The scalability experiments in §5.2 showed a performance decrease of all models with more agents. We analyze the errors made by TWEAC$_{r=1}$ trained on 200 agents from reddit and 171 agents from StackExchange to assess what causes this decrease. We focus on the misclassification errors at rank 1 and count the errors for the different unique mistakes symmetrical, i.e., errors that mistake agent A for agent B and the other way around are both counted towards A-B mistakes.

The majority of errors are due to only a few mistakes. In both datasets, around 0.5% of all unique mistakes account for 10% of all errors and every second error is due to less than 10% of all mistakes (detailed numbers in the appendix). The mistakes with the largest number of errors are for StackExchange *english-ell* (english language learner), *cstheory-cs* and *space-astronomy*. For reddit it is *politics-Conservative*, *recipes-food* and *Autos-cars*.

These mistakes are due to selecting agents of forums with very similar topics, e.g., *english* and *ell* overlap considerably in the topics users address in these forums. Mistaking such agents is a reasonable error to make and we show that humans also fail to correctly identify the correct agent for questions where the model failed: We randomly select 50 errors made by the model each from reddit and StackExchange and ask three expert annotators to select the right agent between the true label and the (wrong) predicted label. On average, they achieve 43% accuracy for reddit and 55% accuracy for StackExchange, indicating that humans are not better than chance to identify the right forum for these questions.

In summary, the lower accuracy with a large number of agents is mainly caused by overlapping agents. The evaluation metrics cannot take the overlapping agents into account as we are limited to only one right agent. It is therefore important for future work to design better datasets that take into account that multiple agents can answer a question.

8 Conclusion

We analyzed how to automatically select suitable QA agents specializing in different questions, as an alternative to a single QA system that tries to cover all possible questions. We presented a scalable meta-QA system that allows for a flexible extension with different QA agents. For newly posed questions, we rank agents by their ability to answer them and select the most suitable ones.

To evaluate the QA agent selection task, we created a realistic scenario with QA agents based on different QA tasks, and constructed a large-scale setting with hundreds of agents using public forums from reddit and StackExchange. We have established that similarity-based methods and our newly proposed approach TWEAC are scalable, extensible, and sample efficient. To allow for a fast integration of new QA agents, we presented a *half-and-half* sampling strategy, which extends TWEAC without full re-training using just a fraction of all available training data.

Future work could further explore the overlap between QA agents with respect to the questions they can answer, e.g., by creating dedicated datasets on QA agent selection. Our current datasets do not account for such overlap, potentially under-estimating the models’ capabilities.
Acknowledgments

This work has been supported by multiple sources. (1) The German Research Foundation through the German-Israeli Project Cooperation (DIP, grant DA 1600/1-1 and grant GU 798/17-1), (2) by the German Federal Ministry of Education and Research and the Hessian Ministry of Higher Education, Research, Science and the Arts within their joint support of the National Research Center for Applied Cybersecurity ATHENE, (3) by European Regional Development Fund (ERDF) and the Hessian State Chancellery – Hessian Minister of Digital Strategy and Development under the promotional reference 20005482 (TexPrax), (4) the German Research Foundation (DFG) as part of the UKP-SQuARE project (grant GU 798/29-1).

We thank Jonas Pfeiffer, Tilman Beck and Leonardo Ribeiro for their insightful feedback and suggestions on a draft of this paper.

References

Omer Anjum, Hongyu Gong, Suma Bhat, Wen-Mei Hwu, and JinJun Xiong. 2019. PaRe: A paper-reviewer matching approach using a common topic space. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 518–528, Hong Kong, China. Association for Computational Linguistics.

Mikhail S. Burtsev, Alexander V. Seliverstov, Rafael Airapetyan, Mikhail Arkhipov, Dilyara Baymurlzina, Nickolay Bushkov, Olga Gureenko, Taras Khakhulin, Yuri Kuratov, Denis Kuznetsov, Alexey Litinskiy, Varvara Logacheva, Alexey Lymar, Valentin Malych, Maxim Petrov, Vadim Polulyakh, Leonid Pugachev, Alexey Sorokin, Maria Vikhreva, and Marat Zaynudtinov. 2018. DeepPavlov: Open-source library for dialogue systems. In Proceedings of ACL 2018, Melbourne, Australia, July 15-20, 2018, System Demonstrations, pages 122–127. Association for Computational Linguistics.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to answer open-domain questions. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1870–1879, Vancouver, Canada. Association for Computational Linguistics.

Alexandr Chernov, Volha Petukhova, and Dietrich Klakow. 2015. Linguistically motivated question classification. In Proceedings of the 20th Nordic Conference of Computational Linguistics, NODAL-IDA 2015, Institute of the Lithuanian Language, Vilnius, Lithuania, May 11-13, 2015, volume 109 of Linköping Electronic Conference Proceedings, pages 51–59. Linköping University Electronic Press / Association for Computational Linguistics.

Christopher Clark, Kenton Lee, Ming-Wei Chang, Tom Kwiatkowski, Michael Collins, and Kristina Toutanova. 2019. BoolQ: Exploring the surprising difficulty of natural yes/no questions. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 2924–2936, Minneapolis, Minnesota. Association for Computational Linguistics.

Daniel Cohen, Liu Yang, and W. Bruce Croft. 2018. Wikipassageqa: A benchmark collection for research on non-factoid answer passage retrieval. In The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, SIGIR ’18, page 1165–1168, New York, NY, USA. Association for Computing Machinery.

Alice Coucke, Alaa Saade, Adrien Ball, Théodore Bluche, Alexandre Cautier, David Leroy, Clément Dumouro, Thibault Gisselbrecht, Francesco Caltagirone, Thibault Lavril, Maël Premet, and Joseph Dureau. 2018. Snips voice platform: an embedded spoken language understanding system for private-by-design voice interfaces. arXiv preprint abs/1805.10190.

Wanyun Cui, Yanghua Xiao, Haixun Wang, Yangqiu Song, Seung-won Hwang, and Wei Wang. 2017. KBQA: learning question answering over QA corpora and knowledge bases. Proceedings of the VLDB Endowment, 10(5):565–576.

Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. 2019. DROP: A reading comprehension benchmark requiring discrete reasoning over paragraphs. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 2368–2378, Minneapolis, Minnesota. Association for Computational Linguistics.

Zhen Duan, Shicheng Tan, Shu Zhao, Qianqian Wang, Jie Chen, and Yanping Zhang. 2019. Reviewer assignment based on sentence pair modeling. Neurocomputing, 366:97 – 108.

Rashmi Gangadharaiah and Balakrishnan Narayanaseamy. 2019. Joint multiple intent detection and slot labeling for goal-oriented dialog. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 564–569, Minneapolis, Minnesota. Association for Computational Linguistics.
Mandy Guo, Yinfei Yang, Daniel Cer, Qinlan Shen, and Noah Constant. 2020. Multireqa: A cross-domain evaluation for retrieval question answering models. arXiv preprint, abs/2005.02507.

Andreas Hanselowski, Christian Stub, Claudia Schulz, Zile Li, and Iryna Gurevych. 2019. A richly annotated corpus for different tasks in automated fact-checking. In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL), pages 493–503, Hong Kong, China. Association for Computational Linguistics.

Dan Hendrycks and Kevin Gimpel. 2016. Bridging nonlinearities and stochastic regularizers with gaussian error linear units. arXiv preprint, abs/1606.08415.

Tsuneo Kato, Atsushi Nagai, Naoki Noda, Ryoysuke Sumitomo, Jianming Wu, and Seiichi Yamamoto. 2017. Utterance intent classification of a spoken dialogue system with efficiently untied recursive autoencoders. In Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue, Saarbrücken, Germany, August 15-17, 2017, pages 60–64. Association for Computational Linguistics.

Young-Bum Kim, Dongchan Kim, Anjishnu Kumar, and Ruhí Sarikaya. 2018. Efficient large-scale neural domain classification with personalized attention. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 1: Long Papers, pages 2214–2224. Association for Computational Linguistics.

Alexandros Komninos and Suresh Manandhar. 2016. Dependency based embeddings for sentence classification tasks. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1490–1500, San Diego, California. Association for Computational Linguistics.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2020. ALBERT: A lite BERT for self-supervised learning of language representations. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net.

Han Li, Jiwhan Lee, Sidharth Mudgal, Ruhí Sarikaya, and Young-Bum Kim. 2019a. Continuous learning for large-scale personalized domain classification. pages 3784–3794.

Zeyu Li, Jyun-Yu Jiang, Yizhou Sun, and Wei Wang. 2019b. Personalized question routing via heterogeneous network embedding. In The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019, pages 192–199. AAAI Press.

Bing Liu and Ian Lane. 2016. Attention-based recurrent neural network models for joint intent detection and slot filling. In Interspeech 2016, 17th Annual Conference of the International Speech Communication Association, San Francisco, CA, USA, September 8-12, 2016, pages 685–689. ISCA.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. arXiv preprint, abs/1907.11692.

Alexander H. Miller, Will Feng, Dhruv Batra, Antoine Bordes, Adam Fisch, Jiase Lin, Devi Parikh, and Jason Weston. 2017. Parlai: A dialog research software platform. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, EMNLP 2017, Copenhagen, Denmark, September 9-11, 2017 - System Demonstrations, pages 79–84. Association for Computational Linguistics.

Sara Mumtaz, Carlos Rodríguez, and Boualem Benatallah. 2019. Expert2vec: Experts representation in community question answering for question routing. In Advanced Information Systems Engineering - 31st International Conference, CAiSE 2019, Rome, Italy, June 3-7, 2019, Proceedings, volume 11483 of Lecture Notes in Computer Science, pages 213–229. Springer.

Preslav Nakov, Doris Hoogeveen, Lluís Márquez, Alessandro Moschitti, Hamdy Mubarak, Timothy Baldwin, and Karin Verspoor. 2017. SemEval-2017 task 3: Community question answering. In Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017), pages 27–48.

Libo Qin, Wanxiang Che, Yangming Li, Haoyang Wen, and Ting Liu. 2019. A stack-propagation framework with token-level intent detection for spoken language understanding. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 2078–2087, Hong Kong, China. Association for Computational Linguistics.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ questions for machine comprehension of text. pages 2383–2392.

Stephen E. Robertson and Hugo Zaragoza. 2009. The probabilistic relevance framework: BM25 and beyond. Foundations and Trends in Information Retrieval, 3(4):333–389.

Salvatore Romeo, Giovanni Da San Martino, Alberto Barrón-Cedeño, and Alessandro Moschitti. 2018. A
flexible, efficient and accurate framework for community question answering pipelines. In Proceedings of ACL 2018, System Demonstrations, pages 134–139, Melbourne, Australia. Association for Computational Linguistics.

Andreas Rücklé and Iryna Gurevych. 2017. End-to-end non-factoid question answering with an interactive visualization of neural attention weights. In Proceedings of ACL 2017, System Demonstrations, pages 19–24, Vancouver, Canada. Association for Computational Linguistics.

Andreas Rücklé, Nafise Sadat Moosavi, and Iryna Gurevych. 2019a. Coala: A neural coverage-based approach for long answer selection with small data. In Proceedings of the 33rd AAAI Conference on Artificial Intelligence (AAAI 2019), pages 6932–6939.

Andreas Rücklé, Nafise Sadat Moosavi, and Iryna Gurevych. 2019b. Neural duplicate question detection without labeled training data. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1607–1617, Hong Kong, China. Association for Computational Linguistics.

Andreas Rücklé, Jonas Pfeiffer, and Iryna Gurevych. 2020. MultiCQA: Zero-shot transfer of self-supervised text matching models on a massive scale. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2471–2486. Online. Association for Computational Linguistics.

Kuldeep Singh, Arun Sethupat Radhakrishna, Andreas Both, Saedeh Shekarpour, Ioanna Lytra, Ricardo Usbeck, Akhilesh Vyas, Christoph Lange, Maria Esther Vidal, Jens Lehmann, and Sören Auer. 2018. Why Reinvent the Wheel: Let’s Build Question Answering Systems Together, page 1247–1256. International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, CHE.

Daniil Sorokin and Iryna Gurevych. 2018. Interactive instance-based evaluation of knowledge base question answering. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 114–119, Brussels, Belgium. Association for Computational Linguistics.

Haitian Sun, Tania Bedrax-Weiss, and William W. Cohen. 2019. PullNet: Open domain question answering with iterative retrieval on knowledge bases and text. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 2380–2390. Association for Computational Linguistics.

Haitian Sun, Bhuwan Dhingra, Manzil Zaheer, Kathryn Mazaitis, Ruslan Salakhutdinov, and William W. Cohen. 2018. Open domain question answering using early fusion of knowledge bases and text. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018, pages 4231–4242. Association for Computational Linguistics.

Alon Talmor and Jonathan Berant. 2019. MultiQA: An empirical investigation of generalization and transfer in reading comprehension. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4911–4921, Florence, Italy. Association for Computational Linguistics.

Yi Tay, Minh C. Phan, Anh Tuan Luu, and Siu Cheung Hui. 2017. Learning to rank question answer pairs with holographic dual LSTM architectures. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, Shinjuku, Tokyo, Japan, August 7-11, 2017, pages 695–704. ACM.

Ricardo Usbeck, Axel-Cyrille Ngonga Ngomo, Bastian Haarmann, Anastasia Krithara, Michael Röder, and Giulio Napolitano. 2017. 7th open challenge on question answering over linked data (QALD-7). In Semantic Web Challenges - 4th SemWebEval Challenge at ESWC 2017, Portoroz, Slovenia, May 28 - June 1, 2017. Revised Selected Papers, volume 769 of Communications in Computer and Information Science, pages 59–69. Springer.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, undefined, Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, undefined, Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, undefined, Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, undefined. 2017. Attention is all you need. In Proceedings of the 31st Conference on Neural Information Processing Systems, NIPS’17, page 6000–6010, Red Hook, NY, USA. Curran Associates Inc.

Kun Xu, Yansong Feng, Songfang Huang, and Dongyan Zhao. 2016. Hybrid question answering over knowledge base and free text. In COLING 2016, 26th International Conference on Computational Linguistics, Proceedings of the Conference: Technical Papers, December 11-16, 2016, Osaka, Japan, pages 2397–2407. ACL.

Wei Yang, Yuqing Xie, Aileen Lin, Xingyu Li, Luchen Tan, Kun Xiong, Ming Li, and Jimmy Lin. 2019. End-to-end open-domain question answering with BERTserini. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations), pages 72–77, Minneapolis, Minnesota. Association for Computational Linguistics.

Yinfei Yang, Daniel Cer, Amin Ahmad, Mandy Guo, Jax Law, Noah Constant, Gustavo Hernandez Abrego, Steve Yuan, Chris Tar, Yun-hsuan Sung, Brian Strope, and Ray Kurzweil. 2020. Multilingual universal sentence encoder for semantic retrieval. pages 87–94.
Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. 2018. HotpotQA: A dataset for diverse, explainable multi-hop question answering. pages 2369–2380.

Wen-tau Yih, Matthew Richardson, Chris Meek, Ming-Wei Chang, and Jina Suh. 2016. The value of semantic parse labeling for knowledge base question answering. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 201–206, Berlin, Germany. Association for Computational Linguistics.

Shu Zhao, Dong Zhang, Zhen Duan, Jie Chen, Yan-Ping Zhang, and Jie Tang. 2018. A novel classification method for paper-reviewer recommendation. Scientometrics, 115(3):1293–1313.
A Appendix

A.1 Inference Time Comparison between Models

Our system should be computationally efficient, i.e., its latency should be low even with a large quantity of QA agents. To estimate the computational efficiency of our approaches, we measure how many queries per second (qps) our model can complete with 10 and 200 agents. TWEAC is tested with both large and base-sized transformers. We index 1000 examples per agent for the similarity-based methods. BM25 is implemented using Elasticsearch\textsuperscript{12} with the default configuration and we use Faiss with a flat index for GPU-based kNN lookup with USE-QA. TWEAC and USE-QA process each question separately without batching to simulate single questions coming in from a user. GPU computation is done on an NVIDIA Titan-RTX GPU.

| QA Agents | Name | QPS |
|-----------|------|-----|
| 10        | TWEAC-R | 49.44± 0.15 |
| 10        | TWEAC-A | 39.44± 0.15 |
| 10        | TWEAC-B | 76.97± 1.15 |
| 10        | USE-QA  | 43.60± 5.01 |
| 10        | BM25    | 232.29±60.19 |
| 200       | TWEAC-R | 46.41± 2.00 |
| 200       | TWEAC-A | 36.39± 0.30 |
| 200       | TWEAC-B | 70.45± 0.76 |
| 200       | USE-QA  | 48.10± 1.67 |
| 200       | BM25    | 221.19±34.52 |

Table 3: Queries per second (qps) of the different methods with 10 and 200 agents. The results are the mean and standard deviation over 5000 and 100.000 iterations for the 10 and 200 agents respectively.

Table 3 shows the results of the measurement. We observe that Elasticsearch is by far the fastest. USE-QA is similar in speed (± 10 qps) to the large TWEAC models.

The choice of transformer architecture has a large impact on TWEAC. TWEAC\textsubscript{A-b} is roughly twice as fast as TWEAC\textsubscript{A-l} which also slower than TWEAC\textsubscript{R-l} as well. We note that there is only a slight increase in the inference time when using TWEAC with 10 and 200 agents.

In conclusion, the model choice presents a trade-off between speed and accuracy: While Elasticsearch with BM25 is considerably faster and requires no GPU, it is also vastly less accurate than the other methods as shown by our experiments. TWEAC\textsubscript{A-b} is 50% faster than TWEAC\textsubscript{R-l} but the latter has a higher performance in all experiments.

A.2 Figure Values

In this section, we present the results to Figure 3, 4 and 5 in table format along with MRR, which is not included in the figures.

| Examples | Name      | Accuracy | MRR  |
|----------|-----------|----------|------|
| 64       | TWEAC-R   | 0.8572   | 0.9153 |
| 64       | TWEAC-A   | 0.8449   | 0.9028 |
| 64       | TWEAC-B   | 0.8271   | 0.8938 |
| 64       | USE-QA    | 0.7143   | 0.8314 |
| 64       | BM25      | 0.6057   | 0.7457 |
| 128      | TWEAC-R   | 0.8934   | 0.9380 |
| 128      | TWEAC-A   | 0.8646   | 0.9174 |
| 128      | TWEAC-B   | 0.8566   | 0.9089 |
| 128      | USE-QA    | 0.7562   | 0.8582 |
| 128      | BM25      | 0.6496   | 0.7762 |
| 256      | TWEAC-R   | 0.9158   | 0.9519 |
| 256      | TWEAC-A   | 0.8980   | 0.9392 |
| 256      | TWEAC-B   | 0.8600   | 0.9074 |
| 256      | USE-QA    | 0.8006   | 0.8826 |
| 256      | BM25      | 0.6939   | 0.8093 |
| 352      | TWEAC-R   | 0.9303   | 0.9606 |
| 352      | TWEAC-A   | 0.9139   | 0.9497 |
| 352      | TWEAC-B   | 0.8621   | 0.9173 |
| 352      | USE-QA    | 0.8189   | 0.8946 |
| 352      | BM25      | 0.7078   | 0.8226 |
| 1024     | TWEAC-R   | 0.9371   | 0.9638 |
| 1024     | TWEAC-A   | 0.9275   | 0.9577 |
| 1024     | TWEAC-B   | 0.9096   | 0.9462 |
| 1024     | USE-QA    | 0.8441   | 0.9092 |
| 1024     | BM25      | 0.7385   | 0.8407 |
| 2048     | TWEAC-R   | 0.9428   | 0.9677 |
| 2048     | TWEAC-A   | 0.9266   | 0.9581 |
| 2048     | TWEAC-B   | 0.8998   | 0.9409 |
| 2048     | USE-QA    | 0.8520   | 0.9149 |
| 2048     | BM25      | 0.7609   | 0.8540 |
| 4096     | TWEAC-R   | 0.9508   | 0.9723 |
| 4096     | TWEAC-A   | 0.9324   | 0.9696 |
| 4096     | TWEAC-B   | 0.9031   | 0.9415 |
| 4096     | USE-QA    | 0.8441   | 0.9092 |
| 4096     | BM25      | 0.7385   | 0.8407 |

Table 4: Table to Figure 3

A.3 Misclassification Analysis

In this section, we present the tables to §7.

\textsuperscript{12}https://www.elastic.co
| QA Agents | Name     | Accuracy | MRR     |
|-----------|----------|----------|---------|
| 10        | TWEACr-i | 0.8346   | 0.8902  |
| 10        | TWEACa-i | 0.7746   | 0.8497  |
| 10        | TWEACa-b | 0.7662   | 0.8436  |
| 10        | USE-QA   | 0.7654   | 0.8500  |
| 10        | BM25     | 0.6664   | 0.7682  |
| 50 TWEAC  | R-l      | 0.6898   | 0.7638  |
| 50 TWEAC  | A-l      | 0.6042   | 0.6967  |
| 50 TWEAC  | A-b      | 0.5980   | 0.6874  |
| 50 USE-QA |          | 0.6232   | 0.7141  |
| 50 BM25   |          | 0.4855   | 0.5824  |
| 100 TWEAC | R-l      | 0.6029   | 0.6872  |
| 100 TWEAC | A-l      | 0.5146   | 0.6186  |
| 100 TWEAC | A-b      | 0.5145   | 0.6049  |
| 100 USE-QA|          | 0.5469   | 0.6394  |
| 100 BM25  |          | 0.4186   | 0.5080  |
| 200 TWEAC | R-l      | 0.5226   | 0.6173  |
| 200 TWEAC | A-l      | 0.4463   | 0.5513  |
| 200 TWEAC | A-b      | 0.4428   | 0.5385  |
| 200 USE-QA|          | 0.4813   | 0.5734  |
| 200 BM25  |          | 0.3604   | 0.4437  |

| QA Agents | Name     | Accuracy | MRR     |
|-----------|----------|----------|---------|
| 50 full training | 0.5980 | 0.6874 |
| 50 no sampling (10) | 0.5028 | 0.5664 |
| 50 half-and-half (10) | 0.5556 | 0.6505 |
| 100 full training | 0.5145 | 0.6049 |
| 100 no sampling (10) | 0.3971 | 0.4542 |
| 100 no sampling (50) | 0.4363 | 0.4954 |
| 100 half-and-half (10) | 0.4406 | 0.5421 |
| 100 half-and-half (50) | 0.4579 | 0.5630 |

| QA Agents | Name     | Accuracy | MRR     |
|-----------|----------|----------|---------|
| 50 full training | 0.6655 | 0.7543 |
| 50 no sampling | 0.6447 | 0.7296 |
| 50 half-and-half | 0.6511 | 0.7458 |
| 100 full training | 0.5914 | 0.6966 |
| 100 no sampling (10) | 0.5541 | 0.6329 |
| 100 no sampling (50) | 0.5900 | 0.6846 |
| 100 half-and-half (10) | 0.5557 | 0.6738 |
| 100 half-and-half (50) | 0.5696 | 0.6834 |

(a) reddit

(b) StackExchange

Table 5: Table to Figure 4.

Table 6: Table to Figure 5 with values for 50 and 100 agents. The starting number of agents for the iterative extension models is indicated in parenthesis.

### Reddit

| QA Agents | Name     | Accuracy | MRR     |
|-----------|----------|----------|---------|
| 10        | TWEACr-i | 0.8648   | 0.9135  |
| 10        | TWEACa-i | 0.8582   | 0.9072  |
| 10        | TWEACa-b | 0.8377   | 0.8964  |
| 10 USE-QA |          | 0.8812   | 0.9275  |
| 10 USE-QA |          | 0.7572   | 0.8453  |
| 50 TWEAC  | R-l      | 0.7339   | 0.8093  |
| 50 TWEAC  | A-l      | 0.6947   | 0.7768  |
| 50 TWEAC  | A-b      | 0.6655   | 0.7543  |
| 50 USE-QA |          | 0.7046   | 0.7952  |
| 50 BM25   |          | 0.5707   | 0.6827  |
| 100 TWEAC | R-l      | 0.6830   | 0.7708  |
| 100 TWEAC | A-l      | 0.6238   | 0.7239  |
| 100 TWEAC | A-b      | 0.5914   | 0.6966  |
| 100 USE-QA|          | 0.6321   | 0.7343  |
| 100 BM25  |          | 0.5027   | 0.6128  |
| 171 TWEAC | R-l      | 0.6285   | 0.7250  |
| 171 TWEAC | A-l      | 0.5604   | 0.6705  |
| 171 TWEAC | A-b      | 0.5288   | 0.6359  |
| 171 USE-QA|          | 0.5636   | 0.6733  |
| 171 BM25  |          | 0.4476   | 0.5544  |

(b) StackExchange

Table 7: Statistics to the misclassification errors and the unique mistakes between agents in §7
| Mistake                        | % of total errors |
|-------------------------------|-------------------|
| politics ↔ Conservative       | 5.50              |
| recipes ↔ food                | 5.09              |
| Autos ↔ cars                  | 4.15              |
| unitedkingdom ↔ ukpolitics    | 4.09              |
| apple ↔ mac                   | 3.72              |
| beer ↔ Coffee                 | 3.21              |
| Anarchism ↔ socialism          | 3.15              |
| dating ↔ seduction            | 3.07              |
| snowboarding ↔ skiing         | 2.97              |
| Games ↔ pcgaming              | 2.95              |
| techsupport ↔ computers       | 2.72              |
| bicycling ↔ motorcycles       | 2.66              |
| soccer ↔ sports               | 2.66              |
| atheism ↔ Christianity        | 2.58              |
| apple ↔ technology            | 2.52              |
| Games ↔ videogames            | 2.50              |
| Buddhism ↔ zen                | 2.23              |
| horror ↔ movies               | 2.17              |
| Marijuana ↔ weed              | 2.17              |
| techsupport ↔ windows         | 2.17              |
| Total Sum                     | 62.27             |

(a) reddit

| Mistake                        | % of total errors |
|-------------------------------|-------------------|
| english ↔ ell                 | 8.49              |
| cstheory ↔ cs                 | 5.50              |
| space ↔ astronomy             | 5.17              |
| hermeneutics ↔ christianity   | 4.64              |
| korean ↔ beer                 | 4.52              |
| sci-fi ↔ movies               | 4.37              |
| windowsphone ↔ android        | 4.00              |
| linguistics ↔ conlang         | 3.90              |
| elementaryos ↔ askubuntu      | 3.87              |
| stats ↔ datascience           | 3.87              |
| superuser ↔ serverfault       | 3.63              |
| monero ↔ bitcoin              | 3.57              |
| homebrew ↔ beer               | 3.26              |
| matheducators ↔ math          | 3.26              |
| security ↔ crypto             | 3.26              |
| unix ↔ askubuntu              | 3.26              |
| skeptics ↔ health             | 3.14              |
| vi ↔ emacs                    | 2.98              |
| movies ↔ literature           | 2.92              |
| physics ↔ astronomy           | 2.89              |
| Total Sum                     | 80.50             |

(b) StackExchange

Table 8: Twenty largest mistakes in §7