Meta Answering for Machine Reading

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Abstract

We investigate a framework for machine reading inspired by real-world information-seeking tasks. Similarly to scrolling through web search results, a meta-answerer inspects the candidate answers to a question provided by a machine reading QA system. We find that with just a small snippet of text around an answer, humans can outperform the underlying QA system. Similarly, a simple machine meta-answerer outperforms the reader on the Natural Questions dataset with equally impoverished information. However, humans and machines seem to differ crucially, in terms of strategies and capacity to use contextual information. Thus, the task suggests a challenge to probe the understanding of context in NLU.

1 Introduction

Question Answering (QA) is a benchmark task in Natural Language Understanding (NLU) that has evolved from a niche evaluation (Voorhees and Tice, 2000) to a yardstick for measuring human vs. computer intelligence (Ferrucci et al., 2010). The dominant format for QA is machine reading (Rajpurkar et al., 2016): answering a question either by extracting a span of text identifying the answer from a single textual context, or abstaining (Rajpurkar et al., 2018).

Machine learning can answer many questions using machine reading, but the price of this setting is artifice, as both the data and the task fail to represent an ideal question answering setup. On the data side, systems can shirk understanding language in favor of artifact-enabled shortcuts, thus making them vulnerable to adversarial attacks (Jia and Liang, 2017; Mudrakarta et al., 2018; Niven and Kao, 2019). On the task side, real-world information-seeking problems such as web search, have different properties; e.g., they are mediated by machines which provide relevant but incomplete and noisy information to a human user. Computers and humans have different skills and different resources (Xie, 2002; Marchionini, 2006; Russell, 2019). Humans can synthesize discrete pieces of information, create long-range strategies, and understand nuanced language. Computers, in contrast, have nigh infinite memory and can take advantage of subtle patterns in their inputs (Wallace et al., 2019).

To put humans and computers on an even playing field, we re-purpose the machine reading task as meta answering (Section 2). A meta-answerer, when presented with the output of a question answering system, must decide which (if any) of the top candidate answers is correct. This task is characterized by imperfect information, since the QA system predictions are noisy. Information is also asymmetric: the meta-answerer and QA system have different views of the data. At the same time, the task is backward-compatible with respect to its original evaluation setup, hence, results are comparable.

We study how humans and computers perform, in both qualitative and quantitative terms, with an existing machine reading (MR) dataset—Natural Questions (Kwiatkowski et al., 2019)—which embeds real users’ information seeking needs in a realistic information retrieval context. Our comparison recapitulates the divergent skills of humans and machines. Humans do better when provided with more information (Section 3) because they discern whether answer candidates are responsive to the question, can solve ambiguous references, and can spot irrelevant distractors that can vex brittle QA systems. In contrast, the machine meta-answerer is overall better at the task (Section 5), besting a BERT (Devlin et al., 2018) reader by two F1 points. It falters, however, when provided with
Thus, meta answering surfaces limitations of NLU and provides insights on different processing strategies: machines are risk-averse, while humans seem naturally inclined to explore. Section 7 discusses how synergies between them could further improve NLU in information-seeking tasks.

2 From Question Answering to Meta-answering

A meta-answerer takes as input the highest scoring answers of an extractive QA system for a given question. The meta-answerer then tries to improve on the underlying system’s result by selecting an answer that possibly differs from the system’s top-scoring one. Formally, an extractive QA system maps a question-context pair \( (q, d) \) to a set of \( M \) answer candidates and their scores, \( \{a_i, \sigma_i\}_{i=1}^M \); all \( a_i \) are subspans of \( d \). In our experiments we use Natural Questions (Kwiatkowski et al., 2019), where \( q \) is a web search query, \( d \) is the highest ranking Wikipedia page returned by Google for \( q \), and each answer candidate is a short span from \( d \).

In web search, a user sees less information, the search results only, compared to the search engine that uses the full document collection. Similarly, a meta-answerer has access to strictly less information than the underlying QA system and lacks direct access to \( d \). Its goal is to find the best answer \( \hat{a} \) within QA’s \( M \)-best candidate list. Again, this resembles a human confronted with a search results composed of links and tiny snippets. Analogously, the QA system returns ‘snippets’ of \( d \) centered on the answer candidates: a window of \( K \) tokens to either side of the answer context. For example, given the question “who did the 49ers beat in the super bowls”, the meta-answerer must decide whether the candidate answer “San Diego Chargers” is the right answer, given the context “The 49ers steamrolled the San Diego Chargers 49 – 26, at”. One of the issues we aim to evaluate is the importance of this additional context for humans and machines.

3 Humans as meta-answerers

To better understand the task and provide a benchmark, we place humans in the role of the meta-answerer. Like the machine meta-answerer in the next section, they see the top candidates from a strong BERT-based (Alberti et al., 2019a) system’s \( M \)-best list and must select which (if any) to provide as the final answer. On one hand, humans have world knowledge that computers do not. However, they are restricted to the same context as computers; they may instead be burdened by their innate knowledge rather than aided.

This section examines how well human meta-answerers can find correct answers in settings with increasing complexity and information; a subset of these settings also correspond to those of our machine meta-answerer.

ANSWERONLY shows only the question and candidate answers without context; the meta-answerer needs to decide whether Central Germany is a reasonable answer to “what culture region is Germany a part of”. CONTEXT adds surrounding context: is “Charles Osgood as the Narrator Jesse McCartney as JoJo, the Mayor’s son” a good answer to “who is JoJo in Horton Hears a Who”. This is identical to the information the machine meta-answerer uses in the next section. REWRITEQUEST goes beyond the machine meta-answerer: users can ask questions to two other QA systems: Lee et al. (2019) over all of Wikipedia or ask the system that generated the \( M \)-best list a different question over the NQ source page. For example, the user asks “Who did Jesse McCartney play in Horton Hears a Who” to verify (the system believes) he plays JoJo.

3.1 Human Answering Framework

A human meta-answerer interacts with the underlying QA system through a text-based interface (Figure 2 in Appendix). They first see a prompt; they can then request an answer from the underlying QA system. After requesting up to 20 examples, the user can either abstain or select one of the answer candidates. For each condition, the same five human meta-answerers (results are averages with error bars) play episodes for random samples of 100 questions from NQ dev questions. In addition, in REWRITEQUEST, the human meta-answerer can ask a different question as an action.

3.2 Comparing Human meta-answerers to NQ Annotators and the QA system

First, however, we need to discuss how to compare human meta-answerers to a traditional QA system or to the humans who created the dataset. NQ uses exact span as an error metric, however

\[1\] Both human and computer meta-answerers also cannot answer questions with disjoint spans; e.g., names from a cast or binary yes/no questions.
### Table 1: A bootstrap evaluation to fairly compare original NQ annotators, human meta-answerers, and the baseline QA system. In the context with the richest interaction, the best human meta-answerer can improve over both the average NQ annotator and the baseline QA system, mostly through improving recall.

|                  | AnswerOnly | Context | RewriteQues |
|------------------|------------|---------|-------------|
|                  | Pr. | Rec. | F1 | Pr. | Rec. | F1 | Pr. | Rec. | F1 |
| NQ annotator     | 57.9 | 46.4 | 51.5 | 51.6 | 57.2 | 57.7 | 45.5 | 50.9 |
| BERT (Alberti et al., 2019b) | 56.4 | 45.7 | 50.5 | 52.9 | 62.7 | 56.4 | 61.4 |
| avg. Human       | 40.7 | 41.1 | 40.6 | 48.9 | 50.9 | 49.8 | 54.5 | 56.7 |
| best Human       | 39.4 | 48.8 | 43.6 | 52.7 | 59.1 | 55.7 | 60.1 | 66.8 |
| ← vs. NQ annotator | -18.5 | 2.4 | -7.9 | -11.5 | 7.5 | -1.5 | 2.4 | 21.3 |
| → vs. BERT       | -17.1 | 3.1 | -6.9 | -7.5 | 11.9 | 2.8 | -7.1 | 10.4 |

Table 2: Ontology for meta-answerer outcomes based on whether a question is answerable. Right and Abstain are “good” outcomes for meta-answerer, while the other outcomes are incorrect. Humans often provide answers when they should not.

|                  | Answerable | Unanswerable |
|------------------|------------|--------------|
|                  | Correctly  | N/A          |
| Answer Wrong     | Neg        | Fool         |
| No Answer        | Dead       | Abstain      |

This does not work for human meta-answerers: our interface shows a span out of context so humans do not know where the string came from. Thus, selecting the correct answer at the wrong position is still counted as a miss (e.g., Kevin Kline at token 13 or 47 is wrong but Kevin Kline at token 30 is correct). To compare the accuracy of the QA system and original NQ annotators (both see the whole source document) with the humans operating on partial knowledge, we compare both exact string matches and partial string matches (surface F1 measuring token overlap).

The first question is whether our human meta-answerer are as good as the original NQ annotators (who see the whole document). NQ provides five annotations of potential answers; and answer “counts” if two NQ annotators agree. For a fair apples to apples comparison, we would need to hold out one NQ annotation and compare it to our human meta-answerers.

Rather than rely on a deficient gold set, bootstrap sample from the remaining four annotations to get back to five annotations. But it would unfair to only evaluate NQ annotators using this, hence we evaluate our humans and the baseline BERT QA system using the same metric (a bootstrap sample to get five annotations). This is a fair comparison between the NQ annotator, our human annotators, and the baseline QA system. Human meta-answerers have lower F1 than both the original annotators as well as the baseline QA system (Table 1), in Context and especially AnswerOnly. All humans improve between AnswerOnly and Context. There is also an improvement from Context to RewriteQues, but formulating new questions also introduces more variance, which is a function of skill. The better human meta-answerers improve over the baseline system. The best human (consistent across all conditions) was −7.9 worse on F1 in the AnswerOnly, the best human meta-answerer has a higher F1 than the average NQ annotator in RewriteQues with substantially less information.

### 3.3 A Taxonomy of Outcomes

The human meta-answerers improve recall far more than precision. To better understand where these gains come from, it’s helpful to go beyond these broad outcomes. To see why human meta-answerers have better recall, we describe possible outcomes of a meta-answerer (Table 2).

**Right and Neg** The clearest result is that the meta-answerer selects a right answer from the QA system and provides it. This can either be confirming the answer that the QA system would have presented, answering when the QA system would have abstained, or selecting a different answer. The most human meta-answerer improvement is to

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3The highest agreement between raters is near 0.7 chance-adjusted $\kappa$, while agreement between the users and the system is typically between 0.5 and 0.6.
Figure 1: Humans improve over the underlying QA as they see more information. They abstain less, but this is often balanced out by being “fooled” (tricked into answering questions where they should abstain). Numbers not comparable to bootstrap evaluation in Table 1.

answer instead of abstaining: 1967 to the question “when did colour tv come out in uk”, the answer is at the top of the baseline QA’s n-best list, but below the threshold.

Sometimes humans select a wrong answer when an answer is available. We call this a negative selection, or “neg” for short. For example, the question “when did the crucifix become the symbol of christianity” has gold answers the 4th century, in the 2nd century, and 4th century. A human meta-answerer selects the 2nd century, which was not an acceptable answer.

Abstain Many NQ instances cannot be answered\(^3\) the next most common outcome is for a meta-answerer to correctly recognize it should not provide a response. The QA system abstains more than humans, which leads to human meta-answerers biggest failing…

Fool The flipside is being “fooled” into answering instead of abstaining; for example answering 3 September to the question “when did the united kingdom entered world war 2”: humans are enticed by the context “after a British ultimatum”. While humans have a much higher rate of being fooled than computers (humans are reluctant to say “I don’t know”), some of this is attributable to annotation problems with NQ.

Dead Sometimes a question is answerable, but the meta-answerer falsely abstains. We call this a “dead” question. Sometimes the meta-answerer is unsure of an answer. For example, for the question “who was fighting in the civil war in england and about what”, the gold answer is “Parliamentarians and Royalists over, principally, the manner of England’s government”. However, humans rejected that answer (perhaps as being too superficial).

Humans improve as we move to the REWRITE-QUEST setting, adding the ability to ask new questions. Human meta-answerers can improve recall by converting baseline abstentions into right answers (and a smaller number of baseline negs). However, humans are more often fooled, resulting in lower average precision (Figure 1). Because the human meta-answerer is at the mercy of the baseline QA system, if the baseline system does not surface the answer, the question will go dead without the ability of the human to find the answer.

3.4 Human Strategies

Without contexts in the ANSWERONLY setting, humans are limited to examining the question answer combination (e.g., knowing that “Germany” is not a part of Central Germany or that Jennifer is not the “meaning of the name Sinead”). However, these cases are rare enough that human meta-answerers do not overall improve the system.

With CONTEXT, human meta-answerers use context to select better answers than the system. For example, seeing that near Arenosa Creek and Matagorda Bay was settled by explorer Robert Cavelier de La Salle in Olympics question, or no Wikipedia page answers “where am I on the steelers waiting list”.

\(^3\)E.g., “universal social services are provided to members of society based on their income or means” is not a question, the NQ source provides an article about Paralympics for an
the Wikipedia page context, allowing to convert a dead model question into a correct one.

With RewriteQues, humans can more thoroughly probe the source document to establish whether an answer is correct. E.g., while the baseline system answers the question “who plays eddie’s father on blue bloods” with Eric Laneuville, humans can explore outside the source document to find the correct answer (William Sadler, who plays Armin Janko, only appears in the sixth season, while the NQ document is about an earlier season) or within the page to establish that Eric Laneuville directed several episodes of Blue Bloods.

4 Machines as meta-answerer

Like the humans, machine meta-answerers inspect and evaluate candidates, based on the available context, and then provide an answer (or abstain). The most salient difference from traditional machine reading systems is that the meta-answerer does not have access to the entire text—it must roughly probe the source document to establish whether an answer is correct. E.g., while the baseline system answers the question “who plays eddie’s father on blue bloods” with Eric Laneuville, humans can explore outside the source document to find the correct answer (William Sadler, who plays Armin Janko, only appears in the sixth season, while the NQ document is about an earlier season) or within the page to establish that Eric Laneuville directed several episodes of Blue Bloods.

4.1 System architecture

Our classifiers are output layers on top of a BERT encoder (Devlin et al., 2018) which translates a semi-structured input into a single dense vector. The $P_A(\cdot \mid q, t, a_i, h)$ is the probability that candidate $a_i$ is a correct answer to question $q$, assuming that the (unobserved) Wikipedia page from which $a_i$ is extracted has title $t$, and an evidence set of hints $h = \{q_1, \ldots, q_K\}$; these inputs are encoded into a dense vector using a BERT model parameterized via $W_E$

$$e_{A}^{(CLS)} = \text{BERT}_{WE}(E(q, t, a_i, h))$$

and then becomes a probability as the output of the feed-forward neural network (FFNN):

$$P_A(\cdot \mid q, t, a_i, h) = \text{FFNN}_{W_A}(e_{A}^{(CLS)}).$$

(2)

The individual hints in the evidence set are chosen by $P_H$ as ‘relevant’ for answering through a similar process. The inputs to evaluate a piece of evidence are the inputs to evaluate a candidate except there is no answer $a_i$, as the goal is for the evidence set to be useful for all candidates. Given this input of question, title, and set of evidence $h$, we create a dense representation

$$e_{H}^{(CLS)} = \text{BERT}(E(q, t, h)),$$

(3)

which, as above, is turned into a probability via a feed-forward network,

$$P_H(\cdot \mid q, t, h) = \text{FFNN}_{W_H}(e_{H}^{(CLS)}).$$

(4)

4.2 Semi-structured Embeddings

An effective input representation for BERT must encode not just individual words but also the role those words play. In Equation 1 and 3, we differentiate the words in the context around an answer and the title of a source page. In addition to an embedding matrix for text tokens $E^T$, we use a top-level segment embedding to distinguish questions $Q$, title $T$, answer candidates $A$, and evidence $O$ (row $S$ in Table 3).

There is a finer distinction within the answer candidates and evidence. We need to separate the context around an answer candidate and the candidate itself (e.g., distinguishing the token “Nigel” from its context in “he voiced Nigel in Rio”). We use sub-segment embedding $E^S$ to distinguish the answer span $a$ and its surrounding left ($e^{(l)}$) and right ($e^{(r)}$) context, within each primary segment type (either Answer $A$ or Evidence $O$). To the text inputs we concatenate the score of the candidate $σ_i$ (row $f$ in Table 3) and finally the position embeddings $E^P$:

$$E_{:,i} = (E_{:,T}; E_{:,S}; E_{:,S'}; F_{i} \times e^{f}, E_{:,P}).$$

(5)

When encoding inputs that should not contain the answers (see below) we mask the respective tokens.

4.3 Answer Candidate Selector

We train $P_A(\cdot \mid q, t, a_i, h)$ with a binary cross-entropy loss, assuming examples of the form
Table 3: Our meta-answerer has three primary components to determine answers, evidence sequences, and impossibility. Each uses a representation from a BERT representation that distinguishes (Segment embedding) the Wikipedia page that contains the answer, the answer candidate, and evidence that encodes alternative candidates as well as the internal structure of the answer and evidence (Segment Embedding). The feature embedding layer captures the strength of the original QA model’s prediction.

\( \langle y, q, t, o, h \rangle \), where \( q \) is a question, \( t \) a page title, \( o = (c^l_i, a_i, c^r_i) \) a binary answer in context, \( h \) the evidence, and a binary label \( y \) indicating whether the answer is a correct answer. We train this classifier using the \( M \)-best list from Alberti et al. (2019b). Because most candidates are wrong, we downsample negative examples.\(^4\)

Selecting the evidence sequence is less straightforward; we describe this in the next section. For the moment, however, let us assume that we have an evidence sequence \( h \) for each question. Then for a \( D \), the answer selector loss \( \mathcal{L}_{A,D}(W_A, W_E) \) is

\[
\sum_{\langle y,q,t,o,h \rangle \in D} -\log P_A(y | q, t, a_i, h; W_A, W_E).
\]

4.4 Evidence Selector

The evidence selector uses \( P_H(\cdot | q, t, h) \)—the probability that \( h \) is a useful sequence of observations to evaluate answers for question \( q \) and title \( t \) using \( P_A \)—to pick, among a set of candidate evidences \( \mathcal{H} \), the sequence \( h \) of length \( M \) that scores the highest.

Training \( P_H \) requires knowing the answer because we want it to score good evidence sequences higher. But we don’t want \( P_H \) to directly depend on the answer. To create an implicit training signal, we induce a pseudo-label that does depend on the answer that is \( 1 \) whenever \( h' \) provides better evidence for determining the correct answer \( d(P_A, q, t, o, y, h, h') \equiv 1[P_A(y | q, t, o, h) < P_A(y | q, t, o, h')] \) (Equation 6)

\[
1[P_A(y | q, t, o, h) < P_A(y | q, t, o, h')]
\]

For readability, we abbreviate Equation 6 as \( d(P_A, h, h') \).

Given this pseudo-label for training, we train \( P_H \) with the answer candidate \( a_i \) masked (Table 3) to allow \( P_H \) to discover useful properties of the evidence to find the correct answer. For a pair of candidate evidences \( h \) and \( h' \), this induces an evidence loss \( \mathcal{L}_{H,D}(W_H, W_E) \) to train \( P_H \),

\[
\sum_{\langle y,q,t,o,h \rangle \in D, h'} [-\log P_H(d(P_A, h, h') | q, t, h; W_H, W_E) - \log P_H(d(P_A, h', h) | q, t, h'; W_H, W_E)].
\]

We generate an alternate evidence \( h' \) by randomly replacing one of the observations in \( h \).\(^5\)

The evidence loss thus maximizes the expected reduction in entropy for \( P_A \) and \( q \) produced by substituting \( h \) with \( h' \). While the full expectation would require summing over all possible answers for \( q \), training on a single answer defines an unbiased (although noisy) estimate of this expectation. The loss and, consequently, the training signal for \( P_H \) implicitly depends on a \( P_A \). However, \( P_A \) and \( P_H \) can be co-trained from scratch.

4.5 Auxiliary impossibility loss

51% of the questions in the NQ dataset are ‘unanswerable’, i.e., there is no gold answer in the context. As demonstrated in the human meta-answerer experiments, learning to abstain is crucial for doing well on NQ.

To help our model detect unanswerable questions, we add an additional impossibility classifier \( P_I \). The impossibility classifier is a single feed-forward layer on top of \( e^{[CLSE]}_A \) (Equation 1) with loss \( \mathcal{L}_{I,D}(W_I, W_E) = \sum_{\langle q,t,h,o \rangle \in D'} -\log P_I(b | q, t, o, h; \Theta_I, \Theta_E) \) (Equation 7)

\(^4\)Different negatives are picked at each epoch so that in expectation all negative examples are seen.

\(^5\)Decoding also selects \( h, h' \) with unit Hamming distance.
Because BERT encoder is used to the input described in Table 3, we ensure our examples and where cotraining $P_H$ size of 32. The pre-training for 200,000 steps, using a batch and randomly masking 30 tokens in each. We run $i$, the evidence set from the top-

We now describe how, at test time, we generate answer predictions. Algorithm 1 uses $P_A$, $P_H$, $P_I$, and MLM: masking one random token from every input. We combine the four losses into a single weighted loss and treat the per-loss weights as hyper-parameters:

$$L = \lambda_A L_A + \lambda_H L_H + \lambda_I L_I + \lambda_{MLM} L_{MLM}$$

**Making predictions** We now describe how, at test time, we generate answer predictions. Algorithm 1 uses $P_A$ and $P_H$ to serve as a meta-answerer on top of an existing QA system. It first builds a size-$k$ evidence set from the top-$k$ answer candidates from the QA system. It then iterates over the remaining $M - k$ candidates using $P_H$ to greedily decide whether to replace observations in the evidence. For example, $h_{i,j}$ is the evidence when the $j^{th}$ element of $h$ has been replaced with observation $a_j$. Once all $M$ candidates have been processed and a $k$-size history $h$ has been selected, we score all candidates using $P_A$ and return their scores. We do not use $P_I$ at test time. Following Alberti et al. (2019a), we always predict the best answer if the score is above a threshold picked on development data.

5 Machine Experiments

5.1 Machine Meta Answering systems

We evaluate three versions of the machine meta-answerers. The first, $MMA_{Base}$, is a baseline to see if a model can pick out the correct answer without context and minimal textual evidence. For each $a_i$ in the $M$-best list of $BERT_{WWM}$, we encode an observation as $(a_i, q, a_1, a_2, \ldots, a_M)$. We annotate $a_i$ with segment id A, the rest with B. Answers and question are separated by [SEP] tokens. Overflowing text is truncated from the end. On the last [CLS] vector we add a binary classifier, corresponding to $P_A$ in Equation (2), trained to identify the gold answer labels for the candidate $a_i$. $MMA_{Base}$ is a vanilla BERT implementation; i.e., without the semi-structured embeddings corresponding to the top two rows of Table 3, without evidence selection and multiple losses described in Sections (4.1-4.6).

We then focus on two full versions of the machine meta-answerers, $MMA_{ANSWER ONLY}$ and $MMA_{CONTEXT}$. As in the human experiments, the former can only see the text of the candidate answer, while the latter can also see a snippet of five tokens to each side of the answer. All losses are trained jointly for 200,000 steps, initializing the encoder with our custom pre-trained BERT large model and randomly initializing $W_A$, $W_I$, and $W_H$. After hyper-parameter search, for $MMA_{ANSWER ONLY}$ we set the $M$-best list size $M = 5$, evidence size $k = 3$, and $w_A = 3, w_H = 0.1, w_I = 10, w_{MLM} = 0$, for the weighted training loss. For $MMA_{CONTEXT}$ we set $M = 4, k = 3, w_A = 3, w_H = 10, w_I = 3, w_{MLM} = 1$.

5.2 Results

Full results on the NQ short answer task are reported in Table 4. We take as reference Alberti et al. (2019b)’s QA model trained on NQ and refer to it as $BERT$. Adding whole word masking (Liu et al., 2019) adds 4.5 F1 points, and we use this $BERT_{WWM}$ as the QA system. The baseline, $MMA_{Base}$, is worse than $BERT_{WWM}$. This shows

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6Nevertheless, co-training $P_I$ is beneficial as this auxiliary training loss helps create representations that better capture whether a question is impossible.
Table 4: Results on the Short Answer task of the Natural Questions dataset.

| System                        | Short Answer Dev | Short Answer Test |
|-------------------------------|------------------|-------------------|
|                               | P     | R      | Span F1 | P     | R      | Span F1 |
| Single annotator (Kwiatkowski et al., 2019) | 63.4  | 52.6  | 57.5   | -    | -      | - |
| BERT (Alberti et al., 2019)  | 59.5  | 47.3  | 52.7   | 63.8  | 44.0   | 52.1 |
| BERTWWM                      | 59.5  | 51.9  | 55.4   | 63.1  | 51.4   | 56.6 |
| MMABase                      | 56.7  | 49.5  | 52.9   | 55.5  | 49.4   | 52.3 |
| MMAAnswerONLY                | 63.1  | 54.3  | 58.4   | 67.3  | 52.4   | 58.9 |
| MMAContext                   | 64.5  | 53.5  | 58.5   | 66.2  | 52.7   | 58.7 |

that a naïve approach to encode evidential information is not comparable with the original answer context. The more careful handling of evidence, embeddings, and multiple losses lead the full MMA systems to outperform MMABase by more than 6 F1 points on test. They also improve over BERTWWM by about 2 F1 points. Interestingly, MMAAnswerONLY outperforms MMAContext on test, particularly on precision (see Appendix A.1 for breakdown), while the latter has slightly better recall. This is counterintuitive, from a human perspective, as humans are better with more information. Together with the additional finding that this is flipped on dev—MMAContext has higher precision and F1 than MMAAnswerONLY—indicates that more work is needed to properly model context.

5.3 Comparing Computers and Humans

In both cases, the meta-answerer works with a stream of answer candidates and tries to improve the top prediction. The computer meta-answerer slightly improves both precision and recall. Qualitatively, the changes are minor: tweaking a span, adding a word, favoring earlier spans, improving the abstention threshold.

Human meta-answerers, however, were more bold. This allows them to greatly improve recall, digging deep in the M-best list to find the answers they believe best answer the question. This exploratory behavior comes at the cost of lower precision; they often get fooled by plausible sounding answers that the NQ annotators did not agree with.

Interestingly, while humans do better when given more context, machine meta-answerers did not. We suspect that the models are still not rich enough for the computer to reason with using the augmented evidence provided in the contexts.

6 Related Work

The work carried out in the early 2000s in the context of the TREC conference,\(^7\), QA track (Voorhees and Tice, 2000) is relevant here. The evaluation of the evidence (candidate answers and their context) is an important aspect of meta answering. The TREC QA framework envisions accounting for answer support as a key part of the task (Voorhees, 2003) and successful systems relied crucially on notions of answer justification (Harabagiu et al., 2000). A substantial difference\(^8\) is that a meta-answerer has no way of affecting the production of evidence (the retrieval step) which is provided by the reader. Also relevant from this body of work, Pizzato and Molla (2005) propose a metasearch QA framework, which relies on several Web search and QA systems. Another relevant line of research involves query reformulation, a popular method among search users (Jansen et al., 2009), mastered also by children (Rutter et al., 2015), which often relies on understanding and reusing the search results context (Huang and Efthimiadis, 2009). Automatic query reformulation has been applied with some success to machine reading. In Nogueira and Cho (2017) and Buck et al. (2018), reinforcement learning (RL) trained agents seek good answers while learning to reformulate questions. Das et al. (2019) propose to perform query reformulation in embedding (continuous) space, and find that it can outperform the surface language reformulations of Buck et al. (2018). We do not consider reformulation here, although it may be a promising direction to explore. More generally, a meta-answerer differs from the methods discussed above in that it does not try to change the candidate list content. In this sense, it is

\(^7\)https://trec.nist.gov/.

\(^8\)Besides the evolution of the machine learning paradigm, and associated size requirements for datasets.
akin to evaluating search results by scrolling down a static result list.

A practical solution to the limited encoding capacity of BERT is to summarize documents. Han et al. (2019) propose an episodic reader that summarizes using RL. Nishida et al. (2019) combine answering and summarization to justify answers, which is effective when explanations are annotated (Yang et al., 2018; Thorne et al., 2018). Yet, there is no evidence that summarization-based readers are competitive in major MR tasks. Similarly related is skim-reading (Seo et al., 2018; Hansen et al., 2019), where documents are only partially encoded for prediction. Skip actions are not supervised and systems are trained with RL. The main advantage is, again, efficiency. Yuan et al. (2019) extend MR by re-purposing existing datasets such as SQuAD and NewsQA (Trischler et al., 2017) for a partially-observed, incremental, QA task. Here an agent is trained with RL for information-gathering and answering actions. However, the performance of such agents is far from competitive.

7 Conclusion

Meta-answering is a framework for QA that attempts to simulate real-world—imperfect—information-seeking tasks, where humans look for answers in settings mediated by machines, using natural language. Human meta-answerers can compete with a BERT-based single system with access to full documents, by only looking at a five token window around candidates. A machine meta-answerer built on BERT can improve the environment’s QA system, thus proving that it is possible to investigate MR in imperfect information settings in high-performance regimes. Further, the task brings to the surface, yet again but from a novel perspective, limitations of the current NLU paradigm. MMA cannot use the contextual information that is effortlessly exploited by humans. Thus, it might prove a suitable framework to advance on these challenges.

For future work, we plan to research the use of reinforcement learning for meta answering. The motivation is two-fold. First, the sequential aspect of information-gathering and answering lend itself naturally to episodic formalization characterized by delayed rewards. Secondly, information seeking tasks might offer challenging and realistic problems for RL. As rewards are sparse, credit assignment is hard.

Language and cognition could help boost progress on more natural learning algorithms (cf. Hung et al. (2019)), for example using imitation learning from human meta-answerers to teach computers more intricate answering and verification strategies. Together, this may allow computers to combine thoroughness with human flexibility and insight.

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Table 5 breaks down the abstain and answer decisions for MMA AnswerOnly and BERTWWM. We find that MMA AnswerOnly is a slightly more accurate abstainer, but that by and large, its tendency to answer or abstain matches that of BERTWWM. However, it is a considerably more accurate answerer – even though it answers 38 times fewer than BERTWWM, it increases the absolute number of correct answers given to by 83 and decreases the number of incorrect answers given by 121, explaining both the higher precision and recall for the NQ evaluation metric.

Table 5: Overall accuracy for the original model and the agent, split by action type.

| Modification       | Loss to Win | Win to Loss |
|--------------------|-------------|-------------|
| Entity Change      | 10          | 6           |
| Different Span     | 1           | 0           |
| Incorrect Span     | 25          | 10          |
| Overall            | 36          | 16          |

Table 6: Classification of cases where the agent’s answer changes correctness.

Additionally, in case of Correct to Incorrect label change, we have found three answers to be incorrectly or doubtfully marked by the raters. Moreover, among all of the cases (35 of them in total) where the algorithm has chosen to pick a different span with the original answer, in 31 of cases the span is shorter. That may indicate that the algorithm finds it more beneficial to avoid all of the unnecessary information from the answer, leading to an overall improvement for the answer statistics. In most of these cases, however, a human would probably judge both of the answers correct. For example, for question What class of ship is the Carnival Glory? the original and deemed correct answer is Conquest - class cruise ship while the one picked by MMA AnswerOnly - Conquest - class is labeled as incorrect by the raters.

Statistics of the answer changes flips from incorrect to correct ("Loss to Win"), and from correct to incorrect ("Win to Loss") are listed in Table 6.
Current question: who built the first temple for god in jerusalem
Document title: Solomon’s Temple
Possible actions are:
[0] Ask ORQA a question.
[1] Ask for answer.
[2] Skip this question
[3] Abstain
[1] Answer: [the temple was constructed under] Solomon [, king of the United] (score: 18.18)
Your choice:

Current question: who built the first temple for god in jerusalem
Document title: Solomon’s Temple
Possible actions are:
[0] Ask ORQA a question.
[1] Ask for answer.
[2] Skip this question
[3] Abstain
[1] Answer: [the temple was constructed under] Solomon [, king of the United] (score: 18.18)
Your choice:

Current question: who built the first temple for god in jerusalem
Document title: Solomon’s Temple
Possible actions are:
[0] Ask ORQA a question.
[1] Ask for answer.
[2] Skip this question
[3] Abstain
[0] Answer: [the temple was constructed under] Solomon [, king of the United] (score: 18.18)
Your choice:

Enter a question to ask BERT: what did solomon build

Current question: who built the first temple for god in jerusalem
Document title: Solomon’s Temple
BERT what did solomon build --> [the First Temple, was] the Holy Temple [\{Hebrew : ′אֵת} (score: 6.34)
Possible actions are:
[0] Ask ORQA a question.
[1] Ask for answer.
[2] Skip this question
[3] Abstain
[1] Answer: [the temple was constructed under] Solomon [, king of the United] (score: 18.18)
[2] Answer: [the temple was constructed under] Solomon , king of the United Kingdom of Israel and Judah [and that during the Kingdom] (score: 18.08)
Your choice:
Correct! You correctly answered ‘Solomon’.

Figure 2: Our interface for human meta-answerer experiments. Users see a question from NQ, see candidates from base QA system, and find their meta answer.