Less is More: Rejecting Unreliable Reviews for Product Question Answering

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Abstract. Promptly and accurately answering questions on products is important for e-commerce applications. Manually answering product questions (e.g. on community question answering platforms) results in slow response and does not scale. Recent studies show that product reviews are a good source for real-time, automatic product question answering (PQA). In the literature, PQA is formulated as a retrieval problem with the goal to search for the most relevant reviews to answer a given product question. In this paper, we focus on the issue of *answerability* and *answer reliability* for PQA using reviews. Our investigation is based on the intuition that many questions may not be answerable with a finite set of reviews. When a question is not answerable, a system should return nil answers rather than providing a list of irrelevant reviews, which can have significant negative impact on user experience. Moreover, for answerable questions, only the most relevant reviews that answer the question should be included in the result. We propose a conformal prediction based framework to improve the reliability of PQA systems, where we reject unreliable answers so that the returned results are more concise and accurate at answering the product question, including returning nil answers for unanswerable questions. Experiments on a widely used Amazon dataset show encouraging results of our proposed framework. More broadly, our results demonstrate a novel and effective application of conformal methods to a retrieval task.

Keywords: Product Question Answering · Unanswerable Questions · Conformal Prediction.

1 Introduction

On e-commerce websites such as Amazon[4] and TaoBao[5], customers often ask product-specific questions prior to a purchase. With the number of product-related questions (queries) growing, efforts to answer these queries manually in real time is increasingly infeasible. Recent studies found that product reviews are a good source to extract helpful information as answers [1–3].

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[4] https://www.amazon.com/.
[5] https://world.taobao.com/.

Table 1. Example of an answerable (Q1) and an unanswerable question (Q2). Green denotes high probability/confidence scores, and red otherwise.

Q1: What is the chain for on the side?			
Top 3 Ranked Reviews	Prob	Conf	Accept
- This was driving me crazy but i see that another reviewer explained that grill has wire clip on chain to be used as extended match holder for igniting the gas if the spark mechanism fails to work or is worn out as sometimes happens with any gas grill.	0.99	0.82	✔
- PS Could not figure out the purpose of that little chain with the clip attached to the outside of the grill - even after reading entire manual.	0.95	0.54	✗
- It is to replace an old portable that I have been using for about 10 years.'	0.91	0.40	✗
Q2: Does this Dell Inspiron 14R i14RMT-7475s come with dell's warranty?			
Top 3 Ranked Reviews	Prob	Conf	Accept
- I don't really recommend the PC for people who wants install heavy games programs.	0.74	0.48	✗
- The computer is nice, fast, light, ok.	0.12	0.01	✗
- I bought the computer for my daughter.	0.05	0.00	✗

To illustrate this, in Table 1 Q1 poses a question about the purpose of the chain on the side of a grill, and the first review addresses the question. The core idea of state-of-the-art PQA models is to take advantage of existing product reviews and find relevant reviews that answer questions automatically. In general, most PQA models implement a relevance function to rank existing reviews based on how they relate to a question. Some directly present a fixed number (typically 10) of the top ranked reviews as answers for the question [1–3], while others generate natural-language answers based on the relevant reviews [4, 5].

However, not every question can be answered by reviews: the existing set of reviews may not contain any relevant answers for the question, or a question may be poorly phrased and difficult to interpret and therefore requires additional clarification. Q2 in Table 1 is an example of an unanswerable question. The user wants to know whether the notebook comes with Dell's warranty, but none of the reviews discuss anything about warranty. In such a case, a system should abstain from returning any reviews and forward the question to the product seller. In the PQA literature, the issue of answerability is largely unexplored, and as such evaluation focuses on simple ranking performance without penalising systems that return irrelevant reviews.

That said, the question answerability issue has begun to draw some attention in machine comprehension (MC). Traditionally, MC models assume the correct answer span always exists in the context passage for a given question. As such, these systems will give an incorrect (and often embarrassing) answer when the question is not answerable. This motivates the development of better comprehension systems that can distinguish between answerable and unanswerable questions. Since SQuAD — a popular MC dataset — released its second version [6] which contains approximately 50,000 unanswerable questions, various MC models have been proposed to detect question-answerability in addition to predicting answer span [17–20]. The MC models are trained to first detect whether a question is answerable or unanswerable and then find answers to answerable questions. [23] proposed a risk controlling framework to increase the reliability of MC models, where risks are quantified based on the extent of incorrect predictions, for both answerable and unanswerable questions. Different from MC which always has one answer, PQA is a ranking problem where there can be a number of relevant reviews/answers. As such, PQA is more challenging, and risk models designed for MC cannot be trivially adapted for PQA.

In this paper, we focus on the problem of answer reliability for PQA. Answer reliability is generalisation of answerability. Answerability is a binary classification problem where answerable questions have only one answer (e.g. MC). In our problem setting, a product question can have a variable number of reliable answers (reviews), and questions with nil reliable answers are the unanswerable questions. The challenge is therefore on how we can estimate the reliability of answers. As our paper shows, the naive approach of thresholding based on the predicted probability from PQA models is not effective for estimating the reliability of candidate answers.

We tackle answer reliability by introducing a novel application of conformal predictors as a rejection model. The rejection model [7] is a technique proposed to reduce the misclassification rate for risk-sensitive classification applications. The risk-sensitive prediction framework consists of two models: a classifier that outputs class probabilities given an example, and a rejection model that measures the confidence of its prediction and rejects unconfident prediction. In our case, given a product question, the PQA model makes a prediction on the relevance for each review, and the rejection model judges the reliability for each prediction and returns only reviews that are relevant *and* reliable as answers. As an example, although the positive class probabilities given by the PQA model to the top 3 reviews are very high in Q1 (Table 1), the rejection model would reject the last two because their confidence scores are low. Similarly for Q2, even though the first review has high relevance, the rejection model will reject all reviews based on the confidence scores, and return an empty list to indicate that this is an unanswerable question.

For the PQA models, we explore both classical machine learning models [1] and BERT-based neural models [3]. For the rejection model, we use an Inductive Mondrian Conformal Predictor (IMCP) [8–11]. IMCP is a popular non-parametric conformal predictor used in a range of domains, from drug discov-

ery [12] to chemical compound activity prediction [11]. The challenge of applying a rejection model to a PQA model is how we define the associated risks in PQA. Conventionally, a rejection mode is adopted to reduce the misclassification rate, but for PQA we need to reduce the error of including irrelevant results. We propose to use IMCP to transform review relevance scores (or probabilities) into confidence scores and tune a threshold to minimize risk (defined by an alternative ranking metric that penalises inclusion of irrelevant results), and reject reviews whose confidence scores are lower than the threshold.

To evaluate the effectiveness of our framework in producing relevant and reliable answers, we conduct a crowdsourcing study using Mechanical Turk[6] to acquire the relevance of reviews for 200 product-specific questions on Amazon [1]. We found encouraging results, demonstrating the applicability of rejection models for PQA to handle unanswerable questions. To facilitate replication and future research, we release source code and data used in our experiments.[7]

2   Related Work

In this section, we survey three related topics to our work: product question answering, question answerability and conformal predictors.

2.1   Product Question Answering

Existing studies on product-related question answering using reviews can be broadly divided into extractive approaches [1, 3] and generative approaches [4, 5]. For extractive approaches, relevant reviews or review snippets are extracted from reviews to answer questions, while for the generative approaches natural answers are further generated based on the review snippets. In both approaches, the critical step is to first identify relevant reviews that can answer a given question.

The key challenge in PQA is the lack of ground truth, i.e. there is limited data with annotated relevance scores between questions and reviews. Even with crowdsourcing, the annotation work is prohibitively expensive, as a product question may have a large number of reviews; and more so if we were to annotate at sentence level (i.e. annotating whether a sentence in a review is relevant to a query), which is typically the level of granularity that PQA studies work with [1, 3]. For that reason, most methods adopt a distant supervision approach that uses existing question and answer pairs from an external source (e.g. the community question answer platform) as supervision. The first of such study is the Mixture of Opinions for Question Answering (MOQA) model proposed by [1], which is inspired by the mixture-of-experts classifier [14]. Using answer prediction as its objective, MOQA decomposes the task into learning two relationships: (1) relevance between a question and a review; and (2) relevance between a review and an answer, sidestepping the need for ground truth relevance between a

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[6] https://www.mturk.com/.
[7] https://github.com/zswvivi/ecml_pqa

question and a review. [3] extends MOQA by parameterising the relevance scoring functions using BERT-based models [15] and found improved performance.

Another recent work [2] learns deep representations of words between existing questions and answers. To expand the keywords of a query, the query words are first mapped to their continuous representations and similar words in the latent space are included in the expanded keywords. To find the most relevant reviews, the authors use a standard keyword-based retrieval method with the expanded query and found promising results.

2.2   Unanswerable Questions

There are few studies that tackle unanswerable questions in PQA. One exception is [16], where they develop a new PQA dataset with labelled unanswerable questions. That said, the author frame PQA as a classification problem, where the goal is to find an answer span in top review snippets (retrieved by a search engine), and as such the task is more closely related to machine comprehension.

In the space of MC, question answerability drew some attention when SQuAD 2.0 [6] was released, which includes over 50,000 unanswerable questions created by crowdworkers. Several deep learning MC systems have since been proposed to tackle these unanswerable questions. [17] proposed a read-then-verify system with two auxiliary losses, where the system detects whether a question is answerable and then checks the validity of extracted answers. [18] proposed a multi-task learning model that consists of three components: answer span prediction, question answerability detection and answer verification.

More generally in question answering (QA), Web QA is an open-domain problem that leverages Web resources to answer questions, e.g. TriviaQA [21] and SearchQA [22]. [23] introduced a risk control framework to manage the uncertainty of deep learning models in Web QA. The authors argue that there are two forms of risks, by returning: (1) wrong answers for answerable questions; and (2) any answers for unanswerable questions. The overall idea of their work is similar to ours, although their approach uses a probing method that involves intermediate layer outputs from a neural model, which is not applicable to non-neural models such as MOQA.

2.3   Conformal Predictors

To measure the reliability of prediction for an unseen example, conformal predictors (CP) compares how well the unseen example *conforms* to previously seen examples. Given an error probability ϵ, CP is guaranteed to produce a prediction region with probability $1 - \epsilon$ of containing the true label y, thereby offering a means to control the error rate. CP has been applied to many different areas, from drug discovery [24, 13, 11] to image and text classification [25]. [13] proposed a neural framework using Monte Carlo Dropout [26] and CP to compute reliable errors in prediction to guide the selection of active molecules in retrospective virtual screen experiments. In [25], the authors replace the softmax layer with

CP to predict labels based on a weighted sum of training instances for image and text classification.
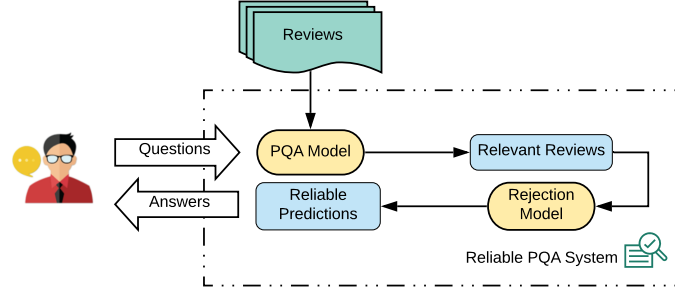
3   Methodology

Fig. 1. Proposed PQA + a rejection model framework.

Our proposed framework consists of two components: a PQA model that predicts the relevance of reviews given a product query, and a rejection model that rejects unconfident reviews and produce only confident reviews as answers. An illustration of our framework is presented in Figure 1.

More specifically, the PQA component (a binary classifier) models the function $\hat{y} = F(r, q)$ where r is a review, q is a product question, and $\hat{y}$ is the probability of the positive class, i.e. the review is relevant to the question.

The rejection model takes the output $\hat{y}$ from the PQA model and transforms it into a confidence score y^*. Given the confidence score, we can then set a significance level $\epsilon \in [0, 1]$ to reject/accept predictions. E.g. if the confidence score of the positive class (review is relevant to the question) is 0.6 and ϵ is 0.5, then we would accept the positive class prediction and return the review as relevant. On the other hand, if ϵ is 0.7, we would reject the review.

3.1   PQA Models

We explore 3 state-of-the-art PQA models for our task:

MOQA [1] is inspired by the mixture-of-experts classifier [14]. In a mixture of experts classifier, a prediction is made by a weighted combination of a number of weak classifiers. Using answer prediction ($P(a|q)$) as its objective, MOQA decomposes the problem into: $P(a|q) = \sum_r P(a|r)P(r|q)$, where a, q, r = answer, query, review respectively. Each review can be interpreted as an "expert", where

it makes a prediction on the answer ($P(a|r)$) and its prediction is weighted by its confidence ($P(r|q)$). The advantage of doing this decomposition is that the learning objective is now $P(a|q)$, which allows the model to make use of the abundance of existing questions and answers on e-commerce platforms. In practice, MOQA is optimised with a maximum margin objective: given a query, the goal is to score a real answer higher than a randomly selected non-answer. To model the two relevance functions ($P(a|r)$ and $P(r|q)$), MOQA uses off-the-shelf pairwise similarity function such as BM25+ and ROUGE-L and a learned bilinear scoring function that uses bag-of-words representation as input features. After the model is trained, the function of interest is $P(r|q)$, which can be used to score a review for a given query. We use the open source implementation and its default optimal configuration.[8]

FLTR [3] is a BERT classifier for answer prediction. Using existing question and answer pairs on e-commerce platforms, [3] fine-tunes a pre-trained BERT to classify answers given a question. After fine-tuning, FLTR is used to classify *reviews* for a given question. FLTR can be seen as a form of zero-shot domain transfer, where it is trained in the (answer, question) domain but at test time it is applied to the (review, question) domain. We use the open-source implementation and its default optimal configuration.[9]

BERTQA [3] is an extension of MOQA, which uses the same mixture of experts framework, but parameterises the relevance functions ($P(a|r)$ and $P(r|q)$) with neural networks: BERT. BERTQA addresses the vocabulary/language mismatch between different domains (e.g. answer vs. review, or review vs. query) using contextualised representations and fine-grained comparison between words via attention. [3] demonstrates that this neural parameterisation substantially improves review discovery compared to MOQA. The downside of BERTQA is its computational cost: while MOQA can be used to compute the relevance for every review for a given query (which can number from hundreds to thousands), this is impractical with BERTQA. To ameliorate this, [3] propose using FLTR to pre-filter reviews to reduce the set of reviews to be ranked by BERTQA.[10]

3.2   Rejection Model

In a classification task, a model could make a wrong prediction for a difficult instance, particularly when the positive class probability is around 0.5 in a binary task. For medical applications such as tumor diagnostic, misclassification

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[8] https://cseweb.ucsd.edu/~jmcauley
[9] https://github.com/zswvivi/icdm_pqa
[10] The original implementation uses a softmax activation function to compute $P(r|q)$ (and so the probability of all reviews sum up to one); we make a minor modification to the softmax function and use a sigmoid function instead (and so each review produces a valid probability distribution over the positive and negative classes).

Table 2. An example of predicted labels with different choices of significance level. p-value for the positive (1) and negative (0) label is 0.65 and 0.45 respectively.

ϵ	Predicted Labels	Outcome
0.05	{0, 1}	Rejected
0.45	{1}	Accepted
0.75	{}	Rejected

can have serious consequences. In these circumstances, rejection techniques are used to reduce misclassification rate by rejecting unconfident or unreliable predictions [7].

To apply rejection techniques to PQA, we need to first understand the associated risks in PQA. There are forms of risks in PQA: (1) including irrelevant reviews as part of its returned results for an answerable question; and (2) returning any reviews for an unanswerable question. This is similar to the risks proposed for Web QA [23], although a crucial difference is that PQA is a ranking problem (output is a list of reviews). The implication is that when deciding the ϵ threshold to guarantee a "error rate", we are using a ranking metric as opposed to a classification metric. As standard ranking metric such as normalised discounted cumulative gain (NDCG) is unable to account for unanswerable questions, we explore alternative metrics (detailed in Section 4.2).

We propose to use conformal predictors (CP) [9, 10] as the rejection model. Intuitively, for a test example, CP computes a nonconformity score that measures how well the new example *conforms* to the previously seen examples as a way to estimate the reliability of the prediction. CP is typically applied to the output of other machine learning models, and can be used in both classification and regression tasks. There are two forms of CP, namely Inductive CP (ICP) and Transductive CP (TCP). The difference between them is their training scheme: in TCP, the machine learning model is updated for each new examples (and so requires re-training) to compute the nonconformity score, while in ICP the model is trained once using a subset of the training data, and the other subset — the *calibration set* — is set aside to be used to compute nonconformity scores for a new example. As such, the associated computation cost for the transductive variant is much higher due to the re-training. We use the Inductive Mondrian Conformal Predictor (IMCP) for our rejection model, which is a modified ICP that is better at handling imbalanced data. When calculating a confidence score, IMCP additionally conditions it on the class label. In PQA, there are typically a lot more irrelevant reviews than relevant reviews for given a query, and so IMCP is more appropriate for our task.

Given a bag of calibration examples $\{(x_1, y_1), ...(x_n, y_n)\}$ and a binary classifier $\hat{y} = f(x)$, where n is number of calibration examples, x the input, y the true label and $\hat{y}$ the predicted probability for the positive label, we compute a nonconformity score, $\alpha(x_{n+1})$, for a new example x_{n+1} using its inverse proba-

bility:

$$\alpha(x_{n+1}) = -f(x_{n+1})$$

As IMCP conditions the nonconformity score on the label, there are 2 non-conformity scores for x_{n+1}, one for the positive label, and one for the negative label:

$$\alpha(x_{n+1}, 1) = -f(x_{n+1})$$
$$\alpha(x_{n+1}, 0) = -(1 - f(x_{n+1}))$$

We then compute the confidence score (p-value) for x_{n+1} conditioned on label k as follows:

$$p(x_{n+1}, k) = \frac{\sum_{i=0}^{n} I(\alpha(x_i, k) \geq \alpha(x_{n+1}, k))}{n + 1} \tag{1}$$

where I is the indicator function.

Intuitively, we can interpret the p-value as a measure of how confident/reliable the prediction is for the new example by comparing its predicted label probability to that of the calibration examples.

Given the p-values (for both positive and negative labels), the rejection model accepts a prediction for all labels k where $p(x_{n+1}, k) > \epsilon$, where $\epsilon \in [0, 1]$ is the significance level. We present an output of the rejection model in Table 2 with varying ϵ, for an example whose p-values for the positive and negative labels are 0.65 and 0.45 respectively. Depending on ϵ, the number of predicted labels ranges from zero to 2. For PQA, as it wouldn't make sense to have both positive and negative labels for an example (indicating a review is both relevant and irrelevant for a query), we reject such an example and consider it an unreliable prediction.

4   Experiments

4.1   Data

We use the Amazon dataset developed by [1] for our experiments. The dataset contains QA pairs and reviews for each product. We train MOQA, BERTQA and FLTR on this data, noting that MOQA and BERTQA leverages both QA pairs and reviews, while FLTR uses only the QA pairs. After the models are trained, we can use the $P(r|q)$ relevance function to score reviews given a product question.

To assess the quality of the reviews returned for a question by the PQA models, we ask crowdworkers on Mechanical Turk to judge how well a review answers a question. We randomly select 200 questions from four categories ("Tools and Home Improvement","Patio Lawn and Garden","Baby" and "Electronics"), and pool together the top 10 reviews returned by the 3 PQA models (MOQA,

Table 3. Answerable question statistics.

Relevance Threshold	2.00	2.25	2.50	2.75	3.00
#Relevant Reviews	640	351	175	71	71
#Answerable Questions	170	134	89	44	44
%Answerable Questions	85%	67%	45%	22%	22%

BERTQA and FLTR),[11] resulting in approximately 20 to 30 reviews per question (total number of reviews = 4,691).[12]

In the survey, workers are presented with a pair of question and review, and they are asked to judge how well the review answers the question on an ordinal scale: 0 (completely irrelevant), 1 (related but does not answer the question), 2 (somewhat answers the question) and 3 (directly answers the question). Each question/review pair is annotated by 3 workers, and the final relevance score for each review is computed by taking the mean of 3 scores.

Given the annotated data with relevance scores, we can set a relevance threshold to define a cut-off when a review answers a question, allowing us to control how precise we want the system to be (i.e. a higher threshold implies a more precise system). We present some statistics in Table 3 with different relevance thresholds. For example, when the threshold is set to 2.00, it means a review with a relevance score less than 2.00 is now considered irrelevant (and so its score will be set to 0.00), and a question where all reviews have a relevance score less than 2.00 is now unanswerable. The varying relevance thresholds will produce a different distribution of relevant/irrelevant reviews and answerable/unanswerable questions; at the highest threshold (3.00), only a small proportion of the reviews are relevant (but they are all high-quality answers), and most questions are unanswerable.

4.2   Evaluation Metric

As PQA is a retrieval task, it is typically evaluated using ranking metrics such as normalised discounted cumulative gain (NDCG) [28]. Note, however, that NDCG is not designed to handle unanswerable queries (i.e. queries with no relevant documents), and as such isn't directly applicable to our task. We explore a variant, NDCG', that is designed to work with unanswerable queries [27]. The idea of NDCG' is to "quit while ahead": the returned document list should be truncated earlier rather than later, as documents further in the list are more likely to be irrelevant. To illustrate this, we present an answerable question in Table 4. Assuming it has three relevant documents (1 represents a relevant

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[11] Following the original papers, a "review" is technically a "review sentence" rather than the full review.

[12] To control for quality, we insert a control question with a known answer (from the QA pair) in every 3 questions. Workers who consistently give low scores to these control questions are filtered out.

Table 4. NDCG' examples.

Question Type	Systems	Doc List	NDCG'
Answerable	System A	111	1.000
	System B	11100	0.971
	System C	11	0.922
Unanswerable	System A	$\emptyset$	1.000
	System B	00	0.500
	System C	000	0.431

document and 0 an irrelevant document), System A receives a perfect NDCG' score while System B is penalised for including 2 irrelevant documents. System C has the lowest NDCG' score as it misses one relevant document. The second example presents an unanswerable question. The ideal result is the empty list ($\emptyset$) returned by System A, which receives a perfect score. Comparing System B to C, NDCG' penalises C for including one more irrelevant document.

NDCG' appends a terminal document (t) to the end of the document list returned by a ranking system. For example, "111" $\rightarrow$ "111t", and "11100" $\rightarrow$ "11100t". The corresponding gain value for the terminal document t is r_t, calculated as follows:

$$r_t = \begin{cases} 1 & \textbf{if } R = 0 \\ \sum_{i=1}^{d} r_i / R & \textbf{if } R > 0 \end{cases}$$

where R is the total number of ground truth relevant documents, and r_i is the relevance of document i in the list. As an example, for the document list "11" produced by System C, $r_t = \frac{1}{3} + \frac{1}{3} = \frac{2}{3}$.

Given r_t, we compute NDCG' for a ranked list of d items as follows:

$$\text{NDCG'}_d = \frac{\text{DCG}_{d+1}\langle r_1, r_2, ..., r_d, r_t \rangle}{\text{IDCG}_{d+1}}$$

With NDCG, for an unanswerable question like the second example, both System B ("00") and System C ("000") will produce a score of zero, and so it fails to indicate that B is technically better. NDCG' solves this problem by introducing the terminal document score r_t.

In practice, the relevance of our reviews is not binary (unlike the toy examples). That is, the relevance of each review is a mean relevance score from 3 annotators, and ranges from 0–3. Note, however, that given a particular relevance threshold (e.g. 2.0), we mark all reviews under the threshold as irrelevant by setting their relevance score to 0.0.

In our experiments, we compute NDCG' up to a list of 10 reviews ($d = 10$), and separately for answerable ($\mathcal{N}_A$) and unanswerable questions ($\mathcal{N}_U$). To aggregate NDCG' over two question types ($\mathcal{N}_{A+U}$), we compute the geometric mean:

$$\mathcal{N}_{A+U} = \sqrt{\mathcal{N}_A \times \mathcal{N}_U}$$

We use geometric mean here because we want an evaluation metric that favours a balanced performance between answerable and unanswerable questions [29]. In preliminary experiments, we found that micro-average measures will result in selecting a system that always returns no results when a high relevance threshold is selected (e.g. ≥ 2.50 in Table 3) since a large number of questions are unanswerable. This is undesirable in a real application where choosing a high relevance threshold means we want a very precise system, and not one that never gives any answers.

4.3   Experimented Methods

We compare the following methods in our experiments:

Vanilla PQA Model: a baseline where we use the top-10 reviews returned by a PQA model (MOQA, FLTR or BERTQA) without any filtering/rejection.

PQA Model+THRS: a second baseline where we tune a threshold based on the review score returned by a PQA model (MOQA, FLTR or BERTQA) to truncate the document list. We use leave-one-out cross-validation for tuning. That is, we split the 200 annotated questions into 199 validation examples and 1 test example, and find an optimal threshold for the 199 validation examples based on $\mathcal{N}_{A+U}$. Given the optimal threshold, we then compute the final $\mathcal{N}_{A+U}$ on the 1 test example. We repeat this 200 times to get the average $\mathcal{N}_{A+U}$ performance.

PQA Model+IMCP: our proposed framework that combines PQA and IMCP as the rejection model. Given a review score by a PQA model, we first convert the score into probabilities,[13] and then compute the p-values for both positive and negative labels (Equation (1)). We then tune the significance level ϵ to truncate the document list, using leave-one-out cross-validation as before. As IMCP requires calibration data to compute the p-value, the process is a little more involving. We first split the 200 questions into 199 validation examples and 1 test examples as before, and within the 199 validation examples, we do another leave-out-out: we split them into 198 calibration examples and 1 validation example, and compute the p-value for the validation example based on the 198 calibration examples. We then tune ϵ and find the optimal threshold that gives the best $\mathcal{N}_{A+U}$ performance on the single validation performance, and repeat this 199 times to find the best overall ϵ. Given this ϵ, we then compute the $\mathcal{N}_{A+U}$ performance on the 1 test example. This whole process is then repeated 200 times to compute the average $\mathcal{N}_{A+U}$ test performance.

4.4   Results

We present the full results in Table 5, reporting NDCG' performances over 4 relevance thresholds: 2.00, 2.25, 2.50, and 2.75.

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[13] This step is only needed for MOQA, as BERTQA and FLTR produce probabilities in the first place. For MOQA, we convert the review score into a probability applying a sigmoid function to the log score.

Table 5. Model performance; boldface indicates optimal $\mathcal{N}_{A+U}$ performance for a PQA model.

Relevance	Model	$\mathcal{N}_{A+U}$	$\mathcal{N}_A$	$\mathcal{N}_U$
	MOQA	0.294	0.309	0.279
	MOQA+THRS	**0.319**	0.212	0.480
	MOQA+IMCP	0.318	0.212	0.477
	FLTR	0.372	0.495	0.279
≥ 2.00	FLTR+THRS	**0.516**	0.400	0.666
	FLTR+IMCP	0.514	0.392	0.675
	BERTQA	0.360	0.464	0.279
	BERTQA+THRS	0.436	0.356	0.534
	BERTQA+IMCP	**0.447**	0.345	0.580
	MOQA	0.264	0.249	0.279
	MOQA+THRS	**0.296**	0.179	0.489
	MOQA+IMCP	0.295	0.163	0.535
	FLTR	0.361	0.468	0.279
≥ 2.25	FLTR+THRS	0.452	0.335	0.608
	FLTR+IMCP	**0.482**	0.329	0.705
	BERTQA	0.344	0.423	0.279
	BERTQA+THRS	0.373	0.293	0.477
	BERTQA+IMCP	**0.405**	0.310	0.530
	MOQA	0.243	0.211	0.279
	MOQA+THRS	**0.274**	0.165	0.453
	MOQA+IMCP	0.265	0.155	0.452
	FLTR	0.359	0.462	0.279
≥ 2.50	FLTR+THRS	0.439	0.326	0.592
	FLTR+IMCP	**0.470**	0.316	0.699
	BERTQA	0.340	0.414	0.279
	BERTQA+THRS	**0.404**	0.308	0.530
	BERTQA+IMCP	0.387	0.294	0.510
	MOQA	**0.235**	0.199	0.279
	MOQA+THRS	0.229	0.129	0.407
	MOQA+IMCP	0.213	0.107	0.423
	FLTR	0.333	0.397	0.279
≥ 2.75	FLTR+THRS	0.409	0.272	0.615
	FLTR+IMCP	**0.416**	0.299	0.577
	BERTQA	0.330	0.390	0.279
	BERTQA+THRS	0.349	0.279	0.435
	BERTQA+IMCP	**0.388**	0.296	0.509

We'll first focus on the combined performances ($\mathcal{N}_{A+U}$). In general, all models (MOQA, FLTR and BERTQA) see an improvement compared to their vanilla

Table 6. Reviews produced by FLTR, FLTR+THRS and FLTR+IMCP for an answerable (Q1) and unanswerable (Q2) question.

Q1: How long the battery lasts on X1 carbon touch?	
Ground Truth	[3, 3]
FLTR	[0, 0, 0, 0, 3, 0, 0, 0, 0, 0]
FLTR+THRS	[0, 0, 0, 0, 3, 0, 0, 0]
FLTR+IMCP	[0, 0, 0, 0, 3]
Q2: What type of memory SD card should I purchase to go with this?	
Ground Truth	[ ]
FLTR	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
FLTR+THRS	[0, 0]
FLTR+IMCP	[ ]

model when we tune a threshold (+THRS or +IMCP) to truncate the returned review list, implying it's helpful to find a cut-off to discover a more concise set of reviews. Comparing between the simple thresholding method (+THRS) vs. conformal method (+IMCP), we also see very encouraging results: for both FLTR and BERTQA, +IMCP is consistently better than +THRS for most relevance thresholds, suggesting that +IMCP is a better rejection model. For MOQA, however, +THRS is marginally better than +IMCP. We hypothesize this may be due to MOQA producing an arbitrary (non-probabilistic) score for review, and as such is less suitable for conformal predictors. Comparing between the 3 PQA models, FLTR consistently produces the best performance: across most relevance thresholds, FLTR+IMCP maintains an NDCG' performance close to 0.5.

Looking at the $\mathcal{N}_U$ results, we notice all vanilla models produce the same performance (0.279). This is because there are no relevant reviews for these unanswerable questions, and so the top-10 returned reviews by any models are always irrelevant. When we introduce +THRS or +IMCP to truncate the reviews, we see a very substantial improvement ($\mathcal{N}_U$ more than doubled in most cases) for all models over different relevance thresholds. Generally, we also find that +IMCP outperforms +THRS, demonstrating that the conformal predictors are particularly effective for the unanswerable questions.

That said, when we look at the $\mathcal{N}_A$ performance, they are consistently worse when we introduce rejection (+THRS or +IMCP). This is unsurprising, as ultimately it is a trade-off between precision and recall: when we introduce a rejection model to truncate the review list, we may produce a more concise/shorter list (as we see for the unanswerable questions), but we could also inadvertently exclude some potentially relevant reviews. As such, the best system is one that can maintain a good balance between pruning unreliable reviews and avoiding discarding potentially relevant reviews.

Next, we present two real output of how these methods perform in Table 6. The first question (Q1) is an answerable question, and the ground truth contains

two relevant reviews (numbers in the list are review relevance scores). FLTR returns 10 reviews, of which one is relevant. FLTR+THRS rejects the last two reviews, and FLTR+IMCP rejects three more reviews, producing a concise list of 5 reviews (no relevant reviews were discarded in this case). One may notice both FLTR+THRS and FLTR+IMCP reject predictions but do not modify the original ranking of the returned reviews by FLTR. +THRS tunes a threshold based on original relevance score, and in +IMCP the conversion of class probability to confidence score (p-value) is a monotonic transformation, and as such the original order is preserved in both methods. This also means that if the vanilla model misses a relevant review, the review will not be recovered by the rejection model, as we see here.

The second question (Q2) is an unanswerable question (ground truth is an empty list). FLTR always returns 10 reviews, and so there are 10 irrelevant reviews. FLTR+THRS discards most of the reviews, but there are still two irrelevant reviews. FLTR+IMCP returns an empty list, indicating existing reviews do not have useful information to answer Q2, detecting correctly that Q2 is an unanswerable question.

5   Conclusion

PQA is often formulated as a retrieval problem with the goal to find the most relevant reviews to answer a given product question. In this paper, we propose incorporating conformal predictors as a rejection model to a PQA model to reject unreliable reviews. We test 3 state-of-the-art PQA models, MOQA, FLTR and BERTQA, and found that incorporating conformal predictors as the rejection model helps filter unreliable reviews better than a baseline approach. More generally, our paper demonstrates a novel and effective application of conformal predictors to a retrieval task.

Acknowledgement

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