App-Aware Response Synthesis for User Reviews

Umar Farooq*, A.B. Siddique*, Fuad Jamour, Zhijia Zhao, Vagelis Hristidis
University of California, Riverside
Email: ufaroo001@ucr.edu, msidd005@ucr.edu, fuadj@ucr.edu, zhijia@cs.ucr.edu, vagelis@cs.ucr.edu

Abstract—Hundreds of thousands of mobile app users post their reviews online. Responding to user reviews promptly and satisfactorily improves application ratings, which is key to application popularity and success. The proliferation of such reviews makes it virtually impossible for developers to keep up with responding manually. To address this challenge, recent work has shown the possibility of automatic response generation by training a seq2seq model with a large collection of review-response pairs. However, because the training review-response pairs are aggregated from many different apps, it remains challenging for such models to generate app-specific responses, which, on the other hand, are often desirable as apps have different features and concerns. Solving the challenge by simply building an app-specific generative model per app (i.e., training the model with review-response pairs of a single app) may be insufficient because individual apps have limited review-response pairs, and such pairs typically lack the relevant information needed to respond to a new review.

To enable app-specific response generation, this work proposes AARSYNTH: an app-aware response synthesis system. The key idea behind AARSYNTH is to augment the seq2seq model with information specific to a given app. Given a new user review, AARSYNTH first retrieves the top-K most relevant app reviews and the most relevant snippet from the app description. The retrieved information and the new user review are then fed into a fused machine learning model that integrates the seq2seq model with a machine reading comprehension model. The latter helps digest the retrieved reviews and app description. Finally, the fused model generates a response that is customized to the given app. We evaluated AARSYNTH using a large corpus of reviews and responses from Google Play. The results show that AARSYNTH outperforms the state-of-the-art system by 22.2% on BLEU-4 score. Furthermore, our human study shows that AARSYNTH produces a statistically significant improvement in response quality compared to the state-of-the-art system.

Index Terms—App reviews, response generation, neural machine translation.

I. INTRODUCTION

The wide adoption of smartphones has created a large and growing market for mobile apps. Recent studies [1] predicted that the number of smartphone users will reach 3.8 billion worldwide by 2021, projecting a market of trillion dollars for mobile apps by 2023. These apps are typically distributed through app stores such as Apple App Store and Google Play. App stores allow users to give their feedback, ask questions, and publicly express their levels of satisfaction with an app through reviews and ratings: positive reviews and ratings are important factors to acquire and retain users. App developers can respond to user feedback to maintain and improve their app reviews and ratings. According to Google Play, responding

*Equal contribution.
review-response pairs for the given app to reliably train a generative model. Second, appropriate responses may not be available in any of the existing training pairs. To address the first challenge, we leverage the review-response pairs from other apps. For the second challenge, we propose to feed the generative model with the most relevant snippets extracted from the app’s description and its existing user reviews — important sources of information that have been neglected or under-utilized by prior work. In fact, our analysis of 10 trending apps on Google Play revealed that 50% of the analyzed apps provide FAQ sections in their app description and 32.3% have reviews with snippets closely relevant to answer app-specific questions raised in other reviews of the same app. Our system AARSYNTH addresses the two challenges as follows.

Figure 2 shows an overview of AARSYNTH. Given a new user review for an app, our information retrieval (IR) module first retrieves relevant text snippets from the app’s description and existing user reviews. Then, the snippets fusion layer uses these snippets to build a review-aware representation (i.e., a representation of the snippets that is associated with the input review) similarly to machine reading comprehension models [5], [6] (MRC). Finally, the review-aware snippets representation and the input review representation along with other app-specific features produced by our encoder are passed to the decoder to produce an app-specific response.

Note that neither an MRC model nor a seq2seq model by themselves are sufficient for the above task. On one hand, an MRC model typically produces a span text — a substring extracted from a textual document, which is hard to comprehend as the response to a review. On the other hand, despite that a seq2seq model can produce free-form text, it can not use the relevant snippets unless they are transformed into a representation that is aware of the input review. Our fusion between the seq2seq and MRC models resolves the limitations of each model in the context of app response generation.

We evaluated AARSYNTH using a large corpus of reviews, responses, and app descriptions collected from Google Play. The results show that AARSYNTH improves the state-of-the-art system RRGen [3] by 22.2% in BLUE-4 score — a widely used metric for text generation. Moreover, our human study using Amazon Mechanical Turk shows that the responses generated by AARSYNTH better address user concerns, are app-specific, and are more fluent than the responses generated by RRGen with a statistically significant difference.

In summary, this paper makes the following contributions:

- It proposes a novel neural architecture that fuses seq2seq and machine reading comprehension models to synthesize free-form responses specific to an app.
- It releases a large dataset [1] that consists of more than 570K review-response pairs and more than 2 million user reviews for 103 popular applications.
- It conducts extensive experimental analysis using the large dataset and compares AARSYNTH against the state-of-the-art systems. The evaluation using automatic metrics and real-user studies confirms the competitiveness of AARSYNTH with a statistically significant improvement.

In the following, we first give the background on attentional encoder-decoder models and information retrieval techniques in Section II. Then, we present AARSYNTH in Section III followed by our experimental setup (Section IV) and the evaluation (Section V). Finally, we discuss the related work in Section VI and conclude this work in Section VII.

II. BACKGROUND

AARSYNTH is built upon the seq2seq neural networks and the state-of-the-art information retrieval techniques. This section offers a brief introduction to these topics.

A. Attentional Encoder-Decoder Model

The goal of an encoder-decoder model, like seq2seq [4], is to synthesize the target sequence (e.g., developer response) \( Y = (y_1, y_2, \ldots, y_m) \) from an input sequence (e.g., user review) \( X = (x_1, x_2, \ldots, x_n) \), where \( m \) and \( n \) are target and input sequence lengths. Figure 3 presents an overview of the seq2seq model, which mainly includes an encoder and a decoder at the high level.

**Encoding.** The encoder reads an input sequence of length \( n \), one token at a time until it encounters the end of sequence token (i.e., \( <\text{eos}> \)). It transforms the sequence into hidden states \( H = (h_1, h_2, \ldots, h_n) \) by applying a Recurrent Neural Network (RNN), such as Long Short-Term Memory (LSTM) [7]. Specifically, it transforms input token \( x_i \) to hidden

\[ h_i = \text{LSTM}(x_i, h_{i-1}) \]
state $h_i = \text{encoder}(h_{i-1}, \text{emb}(x_i))$, where encoder($\cdot$) is a non-linear mapping function, \text{emb}(x_i) is the word embedding of input token $x_i$, and $h_{i-1}$ is the previous hidden state.

**Decoding.** The decoder is initialized with the encoder’s last hidden state $h_n$ and the start of sequence token (i.e., $<\text{sos}>$), then it utilizes another RNN to generate the target sequence $\hat{y}^t$. The decoder also generates one token at a time, until the end token (i.e., $<\text{eos}>$) is generated. The generation, at time-step $i$, is conditioned on the previously generated words $\hat{y}_{i-1}, ..., \hat{y}_1$, and the decoder’s current hidden state $h'_i$, according to the following probability distribution:

$$P(\hat{y}_i|\hat{y}_{i-1}, ..., \hat{y}_1, X') = \text{softmax}(\text{decoder}(h'_i, \hat{y}_{i-1})),$$

where decoder($\cdot$) is a non-linear mapping function and softmax($\cdot$) converts the given vector into a probability distribution. The encoder-decoder model is trained jointly by minimizing the negative log-likelihood loss of the given $N$ training input-target sequence pairs of the form $(X', Y')$:

$$\mathcal{L}(\theta) = - \min_{\theta} \frac{1}{N} \sum_{i=1}^{N} \log p_{\theta}(Y'|X'),$$

where $\theta$ is a set of trainable parameters estimated using optimization algorithms such as stochastic gradient descent.

**Attentional Decoding.** Attention mechanisms [8] are used in seq2seq models to pay attention to more relevant input tokens while decoding. Figure 4 shows the computation of an attention vector at time-step $i$. While decoding at time-step $i$, the decoder($\cdot$) is not only conditioned on the decoder’s current hidden state $h'_i$ and previous generations $\hat{y}_{i-1}, ..., \hat{y}_1$, but also on the attention context vector $v_i$, which is computed as:

$$v_i = \sum_{k=1}^{n} a_{ik} h_k,$$

where $a_{ik}$ is the attention weight for hidden state $h_k$, capturing how relevant is encoder’s $k$-th hidden state for predicting token $\hat{y}_i$ while considering the decoder’s previous hidden state $h'_{i-1}$. The attention weight $a_{ik}$ at time-step $i$ can be computed as:

$$a_{ik} = \frac{\exp(e_{ik})}{\sum_{j=1}^{n} \exp(e_{ij})},$$

where $e_{ik} = \text{align}(h'_{i-1}, h_k)$ and align($\cdot$) is an alignment model implemented as a Multi-Layer Perception (MLP) unit. The attentional seq2seq neural network is trained jointly. We employ the seq2seq framework as a basic building block in our proposed approach for response synthesis.

**B. Relevant Document Retrieval**

Given a collection of documents (e.g., app description and reviews) and a query (e.g., new review), an IR system returns a subset of documents relevant to the query. Figure 5 illustrates how an IR system works: the system creates an index for the given document collection, based on which it finds relevant document(s) for a given query.

**Document Indexing.** IR systems create inverted indexes to facilitate faster document retrieval. An inverted index consists of a set postings lists; a postings list is a list of individual postings, each of which provides information about occurrences of a term (i.e., word) in the document collection including document id and the number of occurrences of the term in each document that contains the term – term frequency (TF). We use Apache Lucene [9], which uses SkipList [10] to implement postings lists for fast retrieval.

**Searching and Ranking.** IR systems typically use vector space retrieval with Term Frequency-Inverse Document Frequency (TF-IDF) weighting [11]. TF captures the importance of a term in a document, and IDF captures the significance of the term in the whole collection. The BM25 [12] algorithm is widely used by IR systems to improve search engine relevance. BM25 scores a document $D$ for input query $Q$ with terms $q_1, q_2, ..., q_n$ as follows:

$$\text{score}(D, Q) = \sum_{i=1}^{n} \text{IDF}(q_i) \cdot \frac{f(q_i, D) \cdot (k_1 + 1)}{f(q_i, D) + k_1 \cdot (1 - b + b \cdot \frac{|D|}{\text{avgdl}})},$$

Fig. 5: Overview of IR indexing and searching.

Fig. 4: Attention-based seq2seq neural model.
where \( f(q_t, D) \) represents the term frequency of \( q_t \) in the document \( D \), the document \( D \) with length \(|D|\), and \( \text{avgdl} \) is the average document length in the whole collection, \( k_1 = [1.2, 2.0] \) and \( b = 0.75 \). In the context of AARSYNTH, we use IR to retrieve the most relevant text snippets from description and reviews of the given app.

III. APP-AWARE RESPONSE SYNTHESIS

In this section, we present AARSYNTH (see Figure 2 for an overview). In the following, we first introduce the IR module, then provide an overview of the neural model, followed by the details of each of its major components.

A. IR Module

AARSYNTH employs IR module as follows. First, it builds an inverted index for all the app descriptions and reviews. Then, it takes a new user review and the app name as inputs, and retrieves top-k relevant documents (i.e., reviews and description of the given app). To get the most relevant text snippets from the app description and reviews, we leverage Lucene [9] Highlighter and Sentence Detector [13] to extract the most relevant snippets from the retrieved document(s). We refer to these text snippets as relevant snippets.

B. Overview of Neural Model

Figure 6 shows the architecture of the proposed app-aware response synthesis model, which consists of the following components: (i) input encoding layers to transform textual inputs to high dimensional contextual representations; (ii) relevant snippets fusion layer to produce a review-aware representation of the relevant snippets; (iii) attention layers to compute attention weights that capture the significance of tokens in the input review and its relevant snippets; and (iv) sequence decoding layer that fuses all the information from the previous layers to ultimately synthesize an app-aware response. We next explain each component in detail.

C. Input Encoding Layers

**Review Encoder.** To encode an input review \( \mathcal{X} = (x_1, x_2, ..., x_d) \), the review encoder first maps each word \( x_t \) to a high dimensional vector space (i.e., word embedding) \( \text{emb}_t \), then an RNN is utilized to produce a new \( d \)-dimensional representation \( \mathcal{H}^\mathcal{X} = (h_t^1, h_t^2, ..., h_t^d) \in \mathbb{R}^{d \times n} \) of all the tokens in the input review, where LSTM is used as an RNN. The token encoding at time-step \( i \) is computed using an LSTM as follows:

\[
\text{h}_t^i = \text{LSTM}(\text{h}_{t-1}^i, \text{emb}_t^i).
\]

This representation is used by the review attention layer to compute the attention weights vector for the sequence decoder and relevant snippets fusion layer to compute the review-aware representation of the relevant snippets.

**Snippets Encoder.** The relevant snippets are retrieved by our IR module based on the input review and app name, and then passed to the snippets encoder, which produces a new representation \( \mathcal{H}^\mathcal{R} = (h_t^1, h_t^2, ..., h_t^u) \in \mathbb{R}^{d \times u} \) where \( u \) is the total number of tokens in all the retrieved snippets. The representation is the result of concatenating the representations produced by the RNN for each snippet. This representation is used by the relevant snippets fusion layer to compute the importance of the words in the snippets with respect to the given user review \( \mathcal{X} \), and is used by the relevance attention layer to generate an attention weights vector of the relevant snippets.

**Category and Rating Encoders.** The category encoder produces a representation \( h_{c1}^i, h_{c2}^i, ..., h_{cn}^i \) for the category of the app and the rating encoder encodes the review rating into \( \text{h}_r^i \in \mathbb{R}^d \). The final hidden states of these layers are passed to the sequence decoder.

D. Relevant Snippets Fusion Layer

This layer associates and fuses information from the relevant snippets and the words of the input review. First, we compute a similarity matrix \( S \in \mathbb{R}^{u \times n} \) between the encodings of the snippets \( \mathcal{H}^\mathcal{R} \) and the encodings of the review \( \mathcal{H}^\mathcal{X} \), where \( S_{bk} \) (value at row \( b \) and column \( k \)) represents the similarity between the \( b \)-th word in the snippets and \( k \)-th word in the user review, which is computed using \( S_{bk} = \alpha(H_{bk}^R, H_{bk}^X) \in \mathbb{R} \), \( \alpha \) is a function trained to capture the similarity between input vectors \( H_{bk}^R \) and \( H_{bk}^X \), where \( H_{bk}^R \) and \( H_{bk}^X \) are \( b \)-th and \( k \)-th column-vectors of \( H^R \) and \( H^X \) respectively. \( \alpha(r, x) = w^{(c)}_t[r \odot x] + w^{(r)}_t[r \odot x] \), where \( \odot \) is element-wise multiplication, and \( w^{(c)}_t \) is a trainable weight vector. Then, from the similarity matrix \( S \), we can get the most important snippet words with respect to the review, i.e., with the closest similarity to the user review. The attention weights for the snippet words are computed using \( z = \text{softmax} (\text{max}_{ud}(S)) \in \mathbb{R}^d \), where \( \text{max}_{ud} \) represents \( \text{max} \) across columns. Then, the most important words in the snippets with respect to the review \( H^R \in \mathbb{R}^{d \times u} \) can be computed by tiling the operation \( H^R \) across columns \( u \) times.
where \( \mathbf{h}^R = \sum_b \mathbf{z}_b \mathbf{h}^R_b \in \mathbb{R}^d \). The matrix \( \hat{\mathbf{h}}^R \in \mathbb{R}^{d \times n} \) represents the fused information between user review and relevant snippets, i.e., review-aware representation of the snippets. This representation can be thought of an MRC model representation of the snippets that is fused with seq2seq representations in the sequence decoder while synthesizing the response.

### E. Attention Layers

**Review Attention Layer.** This layer computes the attention weights of each token in the review as follows. It takes in encoded representation of the review \( \mathcal{H}^X \) and decoder’s hidden state at previous time-step \( \mathbf{h}^d_{i-1} \), and produces an attention context vector \( \mathbf{v}^i_d \) for decoder at time-step \( i \). The context vector \( \mathbf{v}^i_d \) captures the importance of each hidden state of the review encoder while generating token \( \hat{y}_i \) at time-step \( i \). The details on how to compute the context vector are presented in section [II-A](#).

**Relevance Attention Layer.** This layer produces a representation that enables the decoder to pay more attention to the important words in the relevant snippets while generating the final response. It takes in review-aware representation of the relevant snippets \( \hat{\mathcal{H}}^R \) and decoder’s hidden state at previous time-step \( \mathbf{h}^d_{i-1} \), and computes attention context vector \( \mathbf{v}^i_d \) for decoder at time-step \( i \). The attention context vector \( \mathbf{v}^i_d \) signifies the importance of each hidden state of the review-aware representation produced by relevant snippets fusion layer (Section [III-D](#)) that sequence decoder utilizes while synthesizing the token at time-step \( i \).

### F. Sequence Decoder

The sequence decoder fuses the representations of the review, review rating, and category with the MRC style review-aware representation of snippets to generate the final response. The sequence decoder has a softmax-based linear layer that produces copies of snippet representations at every time-step. The parameter \( B \) controls the number of alternatives. At subsequent time-steps, \( B \) copies of the decoder are created, each receives a different input from the previous time-step and picks multiple alternative choices. Finally, the output that maximizes the joint probability of the response is selected. While this approach is computationally expensive, it has shown better performance than greedy decoding that picks the word with maximum probability at every time-step.

### IV. Experimental Setup

#### A. Dataset

**Data Collection.** We crawled 103 popular apps (those with at least 25K star ratings and at least 100 developer replies) across 23 app categories, and collected over 3.4 million reviews and more than 570K review-response pairs. We collected app name, description, number of star ratings, app category, review text, review time, review rating, developer response, and response time. Thanks to our app selection criteria, we were able to collect reviews with much higher response rate: 14.4% compared to 2.8% in [16].

**Preprocessing.** User reviews often contain noisy data [17]. To mitigate this, we performed the following preprocessing steps: (i) removed non-English reviews and responses using a language detector [18], which ensures a concise and valid vocabulary; (ii) performed standard natural language processing (NLP) preprocessing steps such as conversion of letters to lower case, replacement of numbers with “<number>”, emails and URLs with “<email>” and “<url>”, respectively; (iii) replaced greetings and signatures with “<salutation>” and “<signature>”, respectively, to preserve user anonymity; and (iv) removed reviews and responses with less than four
words since such reviews/responses are not likely to contain useful information. After preprocessing, we obtained 425,618 review-response pairs and 2,077,674 reviews with no response. We found that 47 out of 103 apps overlap with RRGen [3] dataset apps. Next, we applied the same preprocessing steps to the RRGen dataset, which resulted in 145K review-response pairs (out of 309K pairs in the original RRGen dataset). We finally merged the two datasets and the final dataset contains 570,881 review-response pairs.

We randomly split the review-response pairs of our dataset into training (530,872), validation (19,511), and test (19,480 ≈ 3.5% of dataset) sets.

**Dataset Analysis.** Table 1 shows a few examples of user reviews, relevant reviews, and app description snippets from our dataset. The snippets from the relevant reviews and app description contain keywords and similar context that can help synthesize a response. In fact, the relevant snippets in many cases provide partial answers for the given user review. For example, while using the Udemy app (see Table 1), a user was unable to watch a video due to intermittent network coverage on a train ride. In this case, the app description happens to have relevant guidance — “download courses to learn offline”. Luckily, other users who faced a similar issue shared the solution “download lecture videos”.

**B. Evaluation Metrics**

We use quantitative automatic metrics as well as subjective human studies to evaluate the performance of AARSYNTH and the competing systems.

**Automatic Metrics.** BLEU [19] score is a standard automatic metric to evaluate natural language generation solutions such as machine translation. It has been demonstrated to have a positive correlation with human judgements. BLEU-n $(n \in \{1, 2, 3, 4\})$ score $\in [0, 100]$ captures the percentage of the n-grams from the synthesized response $Y$ that also co-occur in the the ground truth $\hat{Y}$, where 0 means no matching n-grams and 100 means a perfect match. We utilize BLEU-4, which is considered a standard metric. Moreover, we evaluate using the recall-based automatic metric ROUGE [20], which measures n-grams overlap between the synthesized response $Y$ and the ground truth $\hat{Y}$. We use ROUGE-L that identifies the longest co-occurrence of n-grams using the Longest Common Subsequence (LCS) [21], which naturally evaluates sentence structure similarity.

**Human Study.** We conducted a subjective human study to evaluate the quality of the responses generated by AARSYNTH and other competing methods with respect to the developer responses. We made use of Amazon Mechanical Turk, a crowdsourcing platform for human evaluation, where human evaluators rate the quality of the response on a scale of 1 – 5, 1 being the worst and 5 being the best. We asked human evaluators to consider three aspects in their evaluations: (i) the response is specific to the app; and (ii) whether the response addresses the concern of the user raised in the input review; (iii) the language fluency and the grammatical correctness of the response. We randomly selected 150 generated responses by AARSYNTH and the competing systems for the same reviews, and each response was scored by five different human evaluators who are familiar with the respective app.

**C. Competing Approaches**

We compare AARSYNTH with two IR baselines, an MRC model R-Net [5], and the state-of-the-art response generation system RRGen [3]. We briefly describe each competing method below:

**IR-Reviews:** This baseline builds an index for the reviews in the training set. For an input review and app name from the test set, it retrieves the most relevant indexed review (i.e., top-1) as a response.

**IR-Response:** This baseline builds an index for the developer responses in the training set. For an input review and app name from the test set, it retrieves the most relevant indexed developer response (i.e., top-1) as a response.

**R-Net [5]:** This system was proposed for machine reading comprehension style question answering, and it achieves state-of-the-art results on SQuAD [22] and MS-MARCO [23] datasets. MRC models require annotated answer spans in a passage (app description and reviews in the context of response synthesis) for supervision, which are not available in our dataset, and acquiring such manual annotations is laborious. We annotated spans using BLEU-2 heuristics: the reviews that achieve the maximum BLEU-2 score with the developer response are considered a span.

R-Net obtains question matching representation of a passage by passing the question and the passage through a GRU, then self-matching attention mechanism is employed to refine the generated representation.

**RRGen [3]:** RRGen uses attention-based seq2seq for producing a response for an input review. It conditions the response generation on app category, rating, review...
likelihood loss with a learning rate of 25 over-fitting to training set). We trained the neural network for RNN that has 212075 outlier analysis, we set the maximum length for the review, comparison.

A. Automatic Metrics

**Performance comparison.** Table I shows the BLEU, ROUGE-L, and n-gram precision for the ground truth and synthesized response.

| Method          | BLEU | ROUGE-L | P1  | P2  | P3  | P4  |
|-----------------|------|---------|-----|-----|-----|-----|
| IR Reviews      | 13.67| 12.76   | 21.49| 15.56| 11.44| 8.56|
| IR Response     | 19.19| 17.99   | 27.18| 20.89| 17.14| 14.88|
| R-Net           | 29.16| 39.92   | 42.89| 29.83| 23.19| 16.72|
| RRGen           | 34.55| 46.26   | 50.38| 37.54| 28.25| 22.63|
| AARSYNTH        | 42.22| 51.89   | 56.99| 44.50| 36.56| 30.83|

**TABLE II: Results on automatic metrics.** $p_n$ represents $n$-gram precision for the ground truth and synthesized response.

length, review sentiment, and a set of dictionary-based keywords. RRGen achieves current state-of-the-art results on BLEU [19] metric for the response generation task. Since RRGen outperformed NNGen [24] and NMT [25] models, we do not consider them as competing approaches in this work. We used RRGen’s open-source implementation in our experiments.

D. Implementation Details

We used Apache Lucene [9] and the BM25 [12] scoring algorithm in our IR module, which retrieves 4 snippets from the relevant user reviews for an app and 1 snippet from the app description. We implemented AARSYNTH in PyTorch [27]. The word embedding dimensions were set to 128 and the vocabulary size was set to 10,000. Based on the word length outlier analysis, we set the maximum length for the review, snippets, app category, rating, and response to 75, 50, 4, 1, and 120, respectively. AARSYNTH uses 128 LSTM units as an RNN that has 2 layers for all the encoders (review, snippets, app rating, and app category encoders) and the decoder. We set the batch size to 128 and the dropout rate to 0.2 (i.e., to avoid over-fitting to training set). We trained the neural network for 25 epochs using Adam Optimizer and employ negative log likelihood loss with a learning rate of 0.01.

V. RESULTS

A. Automatic Metrics

**Effect of hyperparameters.** Table IV shows the effect of adjusting the hyperparameters on the overall performance of AARSYNTH. Configuration 5, which has 128 hidden and word embedding dimensions and uses up to top-5 relevant snippets, outperforms the other configurations. Increasing the size of the hidden units or word embedding dimensions does not necessarily improve the performance; in fact, it sometimes worsens the results (the authors in [3] had a similar observation). We observed that increasing the number of relevant snippets does not improve the responses; thus, we use top-5 snippets in our final model. Additionally, configuration 3 and 5 are similar with one exception: the number of layers. Increasing the number of layers improves the results since more layers can capture better representations. Note that even configuration 1, which produces the worst results among reviews and app descriptions, and produces a review-aware representation that is associated with the input review and its important keywords. The seq2seq model learns from the available review-response training pairs. The seq2seq decoder fuses knowledge from both MRC and seq2seq encoders, and thus learns to synthesize responses that are not only fluent and relevant but also app-aware.

**Ablation study.** Table III shows the effect of each component on AARSYNTH; that is, the table shows the performance of AARSYNTH when certain components are enabled. When only the attention-based seq2seq is enabled, AARSYNTH achieves a 21.36 and 26.19 BLEU and ROUGE-L scores, respectively. Enabling the use of app features such as review rating and app category results in a modest improvement of +2.84 and +9.61 on BLEU score, respectively. While other features such as review length and sentiment may, in principle, improve the performance of the system, it has been confirmed in [3] that such features merely cause small improvements. We highlight that enabling the use of our fused architecture (configuration Att. seq2seq + Description + Review) produces the maximum gain on all the metrics: +16.95 on BLEU and +24.2 on ROUGE-L metrics. Moreover, if no relevant reviews are available for a given app (configuration Att. seq2seq + Rating + Category + Description), AARSYNTH continues to provide better performance compared to the state-of-the-art system RRGen (36.11 vs. 34.55 BLEU scores). Several other configurations are also provided in Table III for completeness.
the reported configurations, outperforms the state-of-the-art system RRGGen. This confirms that our performance is not due to parameter tuning, but rather due to fusing seq2seq and MRC architectures.

B. Human Study

We conducted a human study to evaluate the quality of the responses generated by each of the competing systems from a human perspective. We limit this study to the best performing systems based on the results of the automatic metric evaluation. Specifically, we compare AARSYNTH, R-Net, and RRGGen in this study. We randomly selected 150 input reviews and generated their respective responses using each of the competing systems. For each input review, we randomly selected 5 human evaluators to score the respective responses without knowing which responses were generated by which method or whether the response was produced by a developer. Additionally, we required that the evaluators are familiar with the app whose responses are under investigation; in total, 750 evaluators participated in the evaluations. Evaluators were asked to judge a response based on three criteria: app-specificity, whether it contains information that addresses user concerns, and fluency. We report average scores with confidence intervals for responses generated by developers (our ground truth) and each of the competing systems in Table VI. The responses generated by AARSYNTH achieve the best scores on all the aspects when compared to other generative methods. The statistical significance test result ($p$-value < 0.01) [28] also shows that the responses generated by our method achieve statistically significant improvement on all three criteria when compared with R-Net and RRGGen. Moreover, responses generated by AARSYNTH achieve very close scores to those manually generated by developers. While AARSYNTH produces app-specific high-quality responses, these are often not as fluent as manually written responses. This is a common limitation in most conditional natural language generation tasks. In future, we plan to improve the fluency of AARSYNTH’s responses by incorporating a neural language model. Overall, the results of our human study show that the responses generated by AARSYNTH are not only better than other automatic response generation methods, but also on a par with the developers’ manually generated responses.

C. Sample Responses.

We present in Table VI sample responses generated by app developers, R-Net, RRGGen, and AARSYNTH. In what follows, we highlight several interesting examples. Consider the UC Browser app which offers a download option. When a user faces problems while using this option, AARSYNTH is able to discover the resume feature in the download option through relevant snippets, and it offers a possible solution for the problem by including “try resume again it starts downloading...” in the response. Similarly, AARSYNTH learns whether “clear the cache of the app” can possibly solve the issue for the Adobe Reader app (see Table VI), and forwards this information by assigning high weights for the important keywords to the sequence decoder to generate app-aware responses. This example highlights how AARSYNTH generates app-specific responses. AARSYNTH takes advantage of the ever increasing relevant snippets from other reviews of the same app, which are likely to have answers to other reviews. This enables AARSYNTH to generate responses that directly address user concerns as opposed to responses that are vaguely related to the input review. Consider the input review “that is not free. they told free but not”, where the user is concerned about the app content not being free. AARSYNTH is able to learn that the user concern is about pricing and it communicates a possible remedy by responding with “... you can use free course filter...” (see Table VI).

VI. RELATED WORK

Dialogue Response Generation. Response generation is one of the prominent topics in the field of NLP where a system attempts to provide an answer to a given question [29], [30]. Previous studies [31]–[33] proposed IR systems to retrieve the best matching response for a given question. However, recent machine translation based approaches outperformed IR based techniques in response generation tasks [34]–[36]. Touch your heart [37] proposes to generate tone-aware responses for customer care on social media. RRGGen [3] is the first effort to generate the responses for user reviews on Google Play, which utilizes attention-based seq2seq and other features such as category, review sentiments and so on. Since RRGGen is trained on the review-response pairs of many apps, it can only provide generic responses, and it struggles to answer app-specific reviews. Recently, Google Play also started offering suggested replies [2]. This system also suggests generic replies as others. Moreover, Google Play has not made this model open-source; thus, it is not directly comparable to our work. We utilize snippets from app description and reviews (retrieved through IR module) along with other features to synthesize a fluent and app-aware response that addresses user concerns.

TABLE IV: Effects of different hyperparameters on the performance of AARSYNTH. $L$ is the number of layers, $H$ is the number hidden dimensions, $E$ is the number of embedding dimensions, and $S$ is the number of relevant snippets.

| Sr. # | Configuration | BLEU | ROUGE-L |
|-------|---------------|------|---------|
| 1     | $L=2$, $H=256$, $E = 256$, $S = 5$ | 35.95 | 46.16 |
| 2     | $L=2$, $H=128$, $E = 256$, $S = 5$ | 36.80 | 49.30 |
| 3     | $L=1$, $H=128$, $E = 128$, $S = 5$ | 39.31 | 49.69 |
| 4     | $L=2$, $H=128$, $E = 128$, $S = 10$ | 41.72 | 51.58 |
| 5     | $L=2$, $H=128$, $E = 128$, $S = 5$ | **42.22** | **51.89** |

TABLE V: Human study results: AARSYNTH outperforms all competing systems, and the quality of its responses is close to that of expertly written responses (Developer responses).

| Method | App-specific | Addresses Concern | Fluent |
|--------|--------------|-------------------|--------|
| R-Net  | 2.91±0.041   | 2.881±0.042       | 2.856±0.043 |
| RRGGen | 2.915±0.041  | 2.769±0.044       | 2.957±0.042 |
| AARSYNTH| 3.408±0.038  | 3.403±0.038       | 3.456±0.038 |
| Developer| 3.436±0.039  | 3.420±0.039       | 3.375±0.037 |
**TABLE VI:** Sample user reviews, developer responses and generated responses using R-Net, RRGen and AARSYNTH.

| Review | Method     | Response                                                                                                                                   |
|--------|------------|--------------------------------------------------------------------------------------------------------------------------------------------|
| that is not free. they told free but not | Developer R-Net | &lt;salutation&gt; i'm sorry for the inconvenience you are having with the price on udemy. could you please contact us via &lt;email&gt; so we can assist you better. &lt;/salutation&gt; it certainly sounds frustrating and unpleasant experience. we can look into this for you. let us know by sending a quick note to &lt;url&gt;. &lt;salutation&gt; please send a note us at: &lt;email&gt;. &lt;/salutation&gt; udemy is free, but all online contents are not free. you can use free course filter, please contact us via &lt;email&gt; for further assistance. |
| not able to share selection? you must be joking. this is the de facto standard reader and behaves in such an autistic way. | Developer R-Net | &lt;salutation&gt; we are sorry to hear about your experience with about request you to reach out to us at &lt;url&gt; and we'll take into this. &lt;/salutation&gt; we have facing difficulties with our app. email a concerns, please contact free to contact with support team at &lt;email&gt;. &lt;/salutation&gt; we are sorry to hear about your experience. please clear the cache of app from the phone settings. if you are still unable to make it work, reach out to us at &lt;email&gt; and we'll look into this. |
| fare must be deduce. | Developer R-Net | &lt;salutation&gt; we appreciate your feedback and we be work towards make this better. if there's anything else you can take a look into for you please let us know to &lt;email&gt; so we can further connect. we like to hear into this. please email us at &lt;email&gt;. &lt;/salutation&gt; we love to hear your feedback. we believe that fare must be higher but comfortable rides than others. our team is working on this aspect as well. please contact us directly &lt;email&gt; and &lt;number&gt;. |
| movie downloading stuck at &lt;number&gt; worst app. | Developer R-Net | &lt;salutation&gt; we regret the inconvenience you have experienced. pls send us more details via menu-feedback page(open in uc browser).you may clear cache, change download path, turn on/off cloud boost, change access point and then &lt;url&gt; a nice day dear! &lt;/salutation&gt; we feel sorry for the inconvenience. if you resume again it starts downloading. &lt;/salutation&gt; we are sorry to hear that. if you will contact to &lt;email&gt; with the version from google app. &lt;/salutation&gt; we regret the inconvenience you have experienced. if you try resume again it starts downloading from &lt;number&gt;. if issue persists, we suggest you to visit &lt;url&gt; |
