Exploring Input Representation Granularity for Generating Questions Satisfying Question-Answer Congruence

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Abstract

In question generation, the question produced has to be well-formed and meaningfully related to the answer serving as input. Neural generation methods have predominantly leveraged the distributional semantics of words as representations of meaning and generated questions one word at a time. In this paper, we explore the viability of form-based and more fine-grained encodings such as character or subword representations for question generation.

We start from the typical seq2seq architecture using word embeddings presented by De Kuthy et al. (2020), who generate questions from text so that the answer given in the input text matches not just in meaning but also in form, satisfying question-answer congruence. We show that models trained on character and subword representations substantially outperform the published results based on word embeddings, and they do so with fewer parameters.

Our approach eliminates two important problems of the word-based approach: the encoding of rare or out-of-vocabulary words and the incorrect replacement of words with semantically-related ones. The character-based model substantially improves on the published results, both in terms of BLEU scores and regarding the quality of the generated question. Going beyond the specific task, this result adds to the evidence weighing different form- and meaning-based representations for natural language processing tasks.

1 Introduction

Question generation (QG) is a challenging NLP task, where both language form and meaning play a vital role in the production of questions that have to be well-formed and meaningfully related to the envisaged answer. Neural models have been shown to be very promising for QG, with most recent approaches formulating the task as a sequence learning problem with the goal of mapping a sentence onto a question (e.g., Zhao et al., 2018; Chan and Fan, 2019; Xie et al., 2020). The research typically targets QG in the context of Question Answering, where the task is to generate a question that is related to the information in a given paragraph. The QA task ensures a general functional link between the question and the meaning of the passage that answers it. The datasets designed for such question answering/generation provide paragraph-level contexts for each question that span multiple sentences or even multiple passages. Note that the question here is related to the information expressed in the text passage, not to the way in which this information is structured and expressed in the text.

Consider the example from the SQuAD dataset shown in Figure 1. The first question pertains to the first sentence of the passage. While the concept gravity mentioned in that sentence is needed to answer the question, the question cannot be answered using the first sentence as such. For the second question, the information needed to answer the question is expressed in a sentence that is more in line with the question, but still falls short of the so-called question-answer congruence (Stechow, 1990; Sugawara, 2016) required for the sentence to serve as a direct answer to the question.

Figure 1: Example question-answer pairs from the SQuAD dataset (Rajpurkar et al., 2016)

Complementing QG in the prominent QA context, there are other strands of QG research that aim...
at generating questions that can be answered by a sentence as given in the text, putting a premium on question-answer congruence. This includes QG work in the educational application domain, where the perspective of the question is supposed to reflect the perspective of the author of a given text passage that the student is supposed to learn about (Heilman and Smith, 2010; Heilman, 2011; Rus et al., 2012). Recent work under this perspective includes Stasaski et al. (2021), who propose a neural question generation architecture for the generation of cause-and-effect questions. They extract cause and effect relations from text, which are then used as answers for the neural question generation, aiming at direct question-answer congruence.

A second strand of work for which the relation between the question and the answer sentence as expressed in the text plays a crucial role is the research interested in discourse. An early example of research investigating the role of discourse structure for question generation is Agarwal et al. (2011). They identify discourse relations in a text as cues motivating the generation of a question and then formulate questions that can be answered by the sentences with those discourse relations, while ensuring direct question answer congruence. In a related vein, approaches making use of so-called Questions under Discussion (QuDs) to identify the information structure of a sentence in a given discourse also rely on such a direct relationship between question and answer. In a recent paper pursuing this perspective, De Kuthy et al. (2020) show that a seq2seq based neural approach can successfully generate meaningful, well-formed questions that can function as Questions under Discussion in a formal theory of discourse. Similarly, Pyatkin et al. (2020) showed that using question-answer pairs obtained through crowdsourcing can be used reliably to annotate discourse. Based on their crowdsourced data, they train a pipeline of neural models to directly generate such question-answer pairs from text. The overall goal of question generation supporting discourse analysis is to generate a question for every sentence in a text to explicitly characterize the evolving discourse.

Viewed from the perspective of question generation for tasks requiring question-answer congruence, the QG task in essence consists of two steps: (i) replace the answer phrase in the source sentence with a matching question word and (ii) transform the rest of the sentence into a well-formed question. All the words that the generated question consists of are already given, so only the question word that matches the answer phrase needs to be generated anew. The sentence-question pair in example (1) taken from De Kuthy et al. (2020) illustrates this.

(1) A: Auch Otto Graf Lambsdorf ist gegen zweierlei Wahlrecht.
also Otto Graf Lambsdorf is against double voting rights.
Otto Graf Lambsdorf is also against double voting rights.
Q: Wogegen ist auch Otto Graf Lambsdorf?
what against is also Otto Graf Lambsdorf
What is Otto Graf Lambsdorf against, too?

Except for the answer phrase gegen zweierlei Wahlrecht (‘against double voting rights’), all words from the source sentence reappear in the generated question, including the named entity Otto Graf Lambsdorf. The only new material in the question is the question word wogegen (‘what against’).

While the text thus includes all the language needed to successfully generate the question, for seq2seq-based approaches based on word embeddings, the challenge arises that words present in the source sentence which do not appear in the material the embeddings were trained on are not adequately represented. As admitted in De Kuthy et al. (2020), unknown and rare words are therefore a problem and cannot be correctly generated in the question. Rare words are often replaced by semantically related words that are inappropriate in the given context.

In this paper, we explore an alternative: characters and subwords as form-based and more fine-grained representations of both the input and output of the question generation task. We will show that this avoids the unknown/rare word problem and results in a substantial improvement both in a quantitative BLEU evaluation and in terms of a qualitative analysis of the questions. Going beyond the particular QG task, our results contribute to the general endeavour of exploring the best choices of form or meaning-based input and output representations for neural approaches for a range of NLP tasks depending on their characteristics.

2 Related Work

Traditional question generation approaches that leveraged syntactic structures and linguistic features (Liu et al., 2010; Curto et al., 2012; Heilman, 2011) to define transformation rules on parse trees
are inherently limited in their scope and ability to deal with authentic language data. Deep learning has, in recent years, supplanted such methods given its ability to learn the syntactic and semantic properties and characteristics of language when provided with large amounts of natural language text.

Neural question generation is generally realised as a sequence learning problem, so a sequence-to-sequence (seq2seq) architecture (Sutskever et al., 2014) is a logical fit for this type of task. Here, the encoder network learns the latent representation of the source sentence and the decoder network generates the target question one word at a time. The work done by Du et al. (2017) introduces two such models, which are provided with the source sentence and paragraph-level information that encodes the context of the generated question. Borrowing from reinforcement learning, the work by Kumar et al. (2018) introduces policy gradients along with POS tags and named entity mentions to assign task-specific rewards to the training objective. Pointer-generator networks (Gu et al., 2016; See et al., 2017) with gated self-attention have been deployed to address the problem of rare and out-of-vocabulary words and larger contexts (Zhao et al., 2018).

The neural question generation models mentioned above, and many more in this vein, primarily focus on generating questions in English and consider words to be the atomic unit of meaning. They consequently approach the representation learning and text generation tasks at the word level. This assumption does not necessarily hold for languages such as Chinese, where the individual characters contain rich internal information. Neural language models that are trained on character-level inputs have been shown to capture more salient information about morphology than their word-level counterparts (Huang et al., 2016; Marra et al., 2018). Character-aware question answering systems (Golub and He, 2016; Lukovnikov et al., 2017) have similarly been shown to be resilient to the unknown word problem. To capture and combine information about language form and meaning, Bojanowski et al. (2017) proposed treating words as bags of character n-grams to enrich word embeddings with subword information. Byte-pair encoding (Shibata et al., 1999) has seen a recent resurgence in the context of generative language models where it is employed to perform subword segmentation without the necessity of tokenization or morphological analysis. Subword-level embeddings learned with the help of this method have been competitive in many downstream NLP tasks (Sennrich et al., 2015; Heinzeung and Strube, 2018; Xu et al., 2019).

To test performance and trade-offs between character-, subword-, and word-level representations in the context of question generation, we use the German question generation task proposed by De Kuthy et al. (2020), aimed at generating a Question under Discussion for each sentence in a discourse. The required question-answer congruence with the meaning and form requirements this entails, together with the relative morpho-syntactic richness and partially flexible word order of the German language make it an interesting experimental setting for exploring the potential advantages of character and subword representations.

3 Data

In terms of datasets for neural question generation models, contemporary approaches are generally trained on datasets created in the question answering context. These datasets, such as SQuAD (Rajpurkar et al., 2016), Quac (Choi et al., 2018), and Coqa (Reddy et al., 2019), are not well-suited for training models for tasks requiring high question-answer congruence, and they focus on English. Multilingual datasets like XQUAD (Artetxe et al., 2019), MLQA (Lewis et al., 2019), XNLI (Conneau et al., 2018), and TyDi QA (Clark et al., 2020) are similarly unsuitable as they contain only little data, intended as benchmark for the evaluation of question answering systems.

Given these limitations of the established English datasets for the research goals we are pursuing, we instead obtained the German QA answer corpus created by De Kuthy et al. (2020) and base our explorations on that dataset. The corpus contains 5.24 million sentence-question-answer triples which were generated by a transformation-based question generation system (Kolditz, 2015) on articles from the German newspaper Die Tageszeitung (taz, http://taz.de). The corpus exhibits over 30 different types of questions, the most common of which are wh-questions asking for subject and object phrases (such as who or what questions in English) as well as various types of questions asking for adverbial modifiers (such as, for example, when or where questions). Some typical question-answer pairs will be discussed later in section 5.
4 Our Character and Subword-based Neural QG Approach

As the starting point and baseline of our approach, we take the same basic architecture as De Kuthy et al. (2020), a word-embedding based sequence-to-sequence model (Sutskever et al., 2014) with multiplicative attention (Luong et al., 2015). This was done in order to ensure comparability of our results with theirs. Furthermore, any fundamental changes to the neural architecture – such as using a Transformer (Vaswani et al., 2017) or a pointer-generator (Zhao et al., 2018) network – would make it more difficult to distinguish between any improvements offered exclusively by the change in input representation and those by the change in architecture.

To introduce character– and subword–level tokens, we defined an input pipeline consisting of the following steps: 1) UTF-8 text normalization was performed on the input sentence, 2) the normalized input sentence was parsed using spaCy’s (Honnibal et al., 2020) de_core_news_sm model to perform word-level tokenization and part-of-speech (POS) tagging, 3) a second tokenization pass was performed on each word token to generate character and subword tokens, and 4) each character and subword token pertaining to a given word token was assigned the latter’s POS tag and the answer phrase indicator.

For character-level tokenization, each word was decomposed into a list of its component Unicode codepoints. Subword tokenization was performed with the HuggingFace Tokenizer library (Wolf et al., 2020). The library provides byte-pair encoding (BPE, Shibata et al., 1999) and unigram (Kudo, 2018) tokenization algorithms. BPE first constructs a baseline vocabulary with all unique symbols in a corpus. Then, merge rules that combine two symbols in the base vocabulary into a new symbol are learned iteratively until a desired final vocabulary size is reached. Conversely, unigram tokenization starts with a large initial vocabulary from which it repeatedly removes symbols that have the least effect on a loss function defined over the training data of a unigram language model. To reduce the size of the base vocabulary in both models, base symbols are directly derived from bytes rather than (all) Unicode codepoints. The library also includes the SentencePiece (Kudo and Richardson, 2018) algorithm, which processes the input as raw string sequences obviating the need for pre-tokenization.

Finally, bidirectional LSTM was used as the recurrent unit in the encoder as we expect the contextual information provided by the backward pass to not only enrich the sentential representation learned in the encoder but also lower the effective reduction in learnable parameters caused by the smaller vocabulary sizes of the character- and subword-level models. The per-timestep input to the encoder is the concatenation of the token embedding, POS embedding, and the answer phrase indicator. The final outputs of the encoder (hidden state, sequences, cell state) is the concatenation of the respective backward and forward layers of each output.

For the character-level models, a fixed-size vocabulary consisting of all the unique codepoints in the QA corpus was generated. Similarly, the subword tokenizers were trained on the entire corpus to generate vocabularies with 10K symbols each.1

5 Evaluation

For a comprehensive comparison, we trained five models: a word-level model to replicate De Kuthy et al. (2020), three subword models with different tokenization algorithms (byte-level BPE, SentencePiece BPE, and SentencePiece Unigram), and a character model. All models were trained on the same 400K training samples from the QA corpus for 20 epochs, and validation was performed on 40K samples. For each type of input representation, the model with the lowest validation loss was evaluated on a held-out test set of 15K samples.

For their original model, De Kuthy et al. (2020) implemented a post-processing copy module to replace OOV marker tokens in the generated question with the original tokens from the source sentence; this behaviour was replicated for our word-level model. As model hyperparameters, we used: batch size: 128, encoder: Bi-LSTM, decoder: LSTM, encoder/decoder hidden size: 256/512, encoder/decoder dropout: 0.5, word/subword/character embedding dim: 300, decoder beam search width: 5. Table 1 shows the BLEU scores from comparing the ground-truth questions of the test set with corresponding model-generated questions. We used the standard SacreBLEU library (Post, 2018)2 for the calculation of the BLEU scores.

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1The subword vocabularies also include the base symbols found in the character vocabulary. In both cases, special meta tokens such as unknown, sentence-start and end markers were additionally added to each vocabulary.

2Version 1.4.10 with default parameters.
Table 1: Quantitative evaluation results

| Model                | BLEU 1/2/3/4 | Cumulative |
|----------------------|--------------|------------|
| Word (De Kuthy et al., 2020)  | 93.8/86.5/81.0/76.5 | 84.24 |
| Word (replication)    | 93.8/86.5/81.0/76.5 | 84.20 |
| Subword (Byte BPE)    | 98.2/93.4/89.0/87.4 | 91.97 |
| Subword (SentPiece BPE) | 97.0/91.4/87.3/84.1 | 89.35 |
| Subword (SentPiece Unigram) | 98.1/93.3/89.8/87.2 | 91.76 |
| Character             | 97.2/91.8/88.0/85.1 | 90.18 |
| Subword-level (Byte BPE NoPOS) | 98.0/93.0/89.4/86.7 | 91.48 |
| Subword (SentPiece BPE NoPOS) | 97.8/92.3/88.5/85.7 | 90.67 |
| Subword (SentPiece Unigram NoPOS) | 98.0/92.7/88.9/86.1 | 90.84 |
| Character (NoPOS)     | 97.4/91.8/87.9/84.9 | 90.34 |

5.1 Error Analysis

To analyze the quality of the results produced by our models and compare them to those of the baseline word-level model, we performed a manual evaluation of the questions generated for the same sample of 500 sentences of De Kuthy et al. (2020).

The quality of the generated questions was manually evaluated by two human annotators, both trained linguists and native speakers of German. They were asked to provide a binary judgment: whether the question is well-formed and satisfies question-answer congruence with the source sentence. The two conjoined criteria were expressed in the annotation manual as (i) Well-Formedness: Is the question grammatically correct and would I formulate it that way as a native speaker of German? and (ii) Question-Answer Congruence: Is the question answered by the associated sentence as a whole? The annotators were instructed to take into account all aspects of grammaticality, including word order, verb forms, punctuation, and also spelling and capitalization errors. For the evaluation of question-answer congruence, the annotators checked whether the generated question was answerable by the full source sentence, in particular whether the question word matched the given answer phrase and whether the question did not contain any semantically different words. The resulting annotation showed good inter-annotator agreement ($\kappa = 0.74$).

The results of this evaluation (Table 2) reveal how model performance increases with more fine-grained input granularity. The baseline word-level model posted the worst score among all trained models, generating well-formed questions for only 54.2% of the 500 sentences in the evaluation set. The best subword model improves upon this substantially with 61.0% well-formed questions, and the character model adds a further, small improvement. Curiously, removing POS tags as input features from the subword model results in a slight performance increase, but the opposite for the character model. The effect is even more pronounced in the SentencePiece BPE subword model.

To investigate this further, we performed systematic error analysis of the most frequently encountered errors (Table 3). Note that the overall sums differ slightly from the percentages in Table 2 since one question can contain multiple types of errors.

Table 2: Results per question for the evaluation set

| Model                | Well-formed Questions |
|----------------------|-----------------------|
| Word                 | 54.2%                 |
| Subword (SentPiece Unigram) | 59.6%       |
| Subword (SentPiece Unigram No POS) | 61.0%       |
| Character            | 61.4%                 |
| Character (No POS)   | 59.6%                 |

Despite the post-processing copy mechanism, the questions from the word model still contained...
unknown words in 35 cases. For example, rare words such as süßisant (smug), listenreich (cunning), Naschwerk (sweet delicacy), Erbtanten (rich aunt from which one inherits). The subword and character models did not have this problem at all. Unwanted word replacements with different words occurred in 35 samples with the word model, for example, unbegreiflich (incomprehensible) was replaced by geschehen (happen), Adelheid Streidel (proper name of a terrorist) by extremistischen Streidel (extremist Streidel), and bewilligt (approved) by beantragt (requested). The subword models reduce this to as few as five occurrences, and in the character models this type of error does not occur at all. By far, the biggest error source for all models is the production of incorrect question words. This is a hard objective since the question word depends on aspects of form (e.g., does it refer to a nominal phrase or a prepositional phrase) and meaning (e.g., does it refer to an animate or inanimate referent) of the given answer phrase. The word-level model had fewer problems with question word generation than the other models, so the word embeddings encode sufficient form and meaning information for the model to learn the question word patterns.

There appears to be no single, clear pattern across all models that explains the effect of POS tags. Nevertheless, the quality of question words does consistently suffer when they are removed from the input. The character-based model without POS tags generated the highest number of questions with an incorrect question word - an aspect of question generation that relies on meaning-related information, evidently provided by the latter. One potential explanation could be rooted in how the models process the POS features: By assigning to each subword or character the POS tag of its parent word, the model has to contend with increased noise in the training data due to weak correlation between the tags and specific subwords or characters.

For instance, the subword unit her in herekommen (to come from) would take the latter’s POS tag VB (verb) but will be assigned JJ (adjective) when appearing in herrlich (superb).

To gain a better understanding of when a model generates a new form and when it copies tokens from the input, in the following we discuss indicative examples together with the softmax-activated attention scores between the source sentence and the question. In the figures below, the x-axis and y-axis of each plot correspond to the tokens in the generated question and the source sentence, respectively. Each pixel corresponds to the alignment weight $w_{xy}$ of the y-th source token and x-th target token, ranging from 0 (purple) to 1 (yellow). The red tokens on the y-axis indicate the phrase in the source sentence that answers the question.

Example (2) shows a typical sentence-question pair from the evaluation sample. Both the subword models and the character models produced the correct question in (2-b), given the answer phrase (marked in bold font).

(2) a. Bis dahin seien die Länder der DDR pleite.

  until then would be the states of the GDR bankrupt

b. Wer ist bis dahin pleite?

  who is until then bankrupt

For the correct question (2-b), the models have to produce the question word Wer (who) in place of the answer phrase die Länder der DDR (the states of the GDR), and they have to transform
the plural *sehen* (were) into the singular verb *ist* (is). The sentence initial *Bis dahin* (until then) must be placed after the verb and lower cased. The attention plots in Figures 2 and 3 directly showcase this. The tokens in the answer phrase, particularly the first one, have higher alignment weights for the question word than the other tokens in the sentence. Similarly, the model specifically attends to the verb in the source sentence when generating the same in the question. The tokens that are copied as-is from the source sentence have strong, monotonic weights that appear as diagonals.

Example (3) shows another sentence-question pair from the evaluation set. The character model predicted the correct question (3-b), but the subword model predicted the incorrect question (3-c), in which the adverb *danach* (thereafter) is repeated and the numeral 1988 from the input is missing.

(3) a. Danach sollte Ende 1988 mit der Produktion der U-Boote und mit der Teillieferung der Teillieferung begonnen werden.

    Subsequently, production of the submarines and partial deliveries were to begin at the end of 1988.

    b. Womit sollte danach Ende 1988 begonnen werden?

    What should be started thereafter at the end of 1988?

    c. Womit sollte danach Ende danach begonnen werden?

    What should be started thereafter at the end of 1988?

The corresponding attention scores are shown in Figure 4 for the correct question (3-b) generated by the character model and Figure 5 for the erroneous question (3-c) produced by the subword model. Once again, in order to produce the question word *Womit* (with what), both models assign a strong weight to the preposition *mit* (with), which is the first token of the given answer phrase. While the character model then continues to correctly annotate the tokens in the source sentence, the subword model’s alignments show more ambiguity. For the token *danach* (thereafter), it additionally attends to *Ende* (end) in the source sentence - another word that carries a temporal meaning. At the position of the numeral 1988, the model assigns significant weights to all three temporally related words, but the weight for *Ende* is diminished due to its occurrence in the previous timestep. Neverthe-
less, the model ultimately shows higher confidence in *danach* than in the rest and thus (mis-)predicts it a second time.

![Figure 4: Character attention plot for example (3)](image)

One potential problem of a purely form-based approach using characters is that it can produce character strings that do not correspond to any word in the given language. This hardly ever occurred in the questions generated by our character model with the exception of one interesting example where the model created a new question word, illustrated here in example (4).

(4) a. Dies dürfte sich mit der Schaffung des Binnenmarktes ab 1993 ändern. 

*This is likely to change with the creation of the single market from 1993.*

Given the answer phrase *ab 1993*, the model produced the question word *Worab* – a concatenation of the (existing) words *wo* (where) and the preposition *ab* (on) – instead of the required question phrase *ab wann* (from when). Such concatenations of a question word and a preposition actually exist in German, e.g., in the question word *woran* (what of), so the character model apparently picked up this pattern of generating question words from prepositions, but applied it to a non-existing case.

![Figure 5: Subword attention plot for example (3)](image)
6 Conclusion

We explored the prospect of neural question generation at the character- and subword-level using finer-grained input representations than word tokens by adopting De Kuthy et al. (2020)’s task of generating Questions under Discussion for German. The models that were trained on character and subword tokens showed significant leaps in BLEU scores in comparison to the baseline word-level model, even in the absence of extra linguistic information.

In addition to eliminating the problem of out-of-vocabulary and rare words, our manual analysis of the generated questions revealed that those models were able to learn and exploit both semantic and orthographic information with fewer parameters, producing questions with fewer errors relating to word order and word replacement. The character model, in particular, is able to fully eliminate the latter error category.

Considering the relevance of the research beyond the specific question generation task, the results reported in this paper provide further evidence and motivation to consider the advantages of form-focused neural representations and character-level natural language generation for tasks such as machine translation and extractive text summarization.

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