Meta Sequence Learning for Generating Adequate Question-Answer Pairs

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Abstract
Creating multiple-choice questions to assess reading comprehension of a given article involves generating question-answer pairs (QAPs) on the main points of the document. We present a learning scheme to generate adequate QAPs via meta-sequence representations of sentences. A meta sequence is a sequence of vectors comprising semantic and syntactic tags. In particular, we devise a scheme called MetaQA to learn meta sequences from training data to form pairs of a meta sequence for a declarative sentence (MD) and a corresponding interrogative sentences (MIs). On a given declarative sentence, a trained MetaQA model converts it to a meta sequence, finds a matched MD, and uses the corresponding MIs and the input sentence to generate QAPs. We implement MetaQA for the English language using semantic-role labeling, part-of-speech tagging, and named-entity recognition, and show that, trained on a small dataset, MetaQA generates efficiently over the official SAT practice reading tests a large number of syntactically and semantically correct QAPs with over 97% accuracy.

1 Introduction
In an effort to build an online learning tool for helping students improve reading comprehension, it calls for a system to automatically generate adequate multiple-choice questions (MCQs) to assess student’s understanding of a given article’s main points. An article’s main points include direct and derived points. A direct point is expressed in a declarative sentence. A derived point is inferred from multiple direct points, which could be a causal relation between them, an aggregation over them, or a conclusion drawn from them.

We study automatic generation of question-answer pairs (QAPs) with an emphasis on the grammatical correctness of the questions and the suitability of the answers. By grammatical correctness we mean that the questions being generated are syntactically and semantically correct and conform to what a native speaker would say. We refer to such QAPs as adequate QAPs. Other tasks of generating MCQs not addressed in this paper are how to provide adequate distractors for an answer.

Existing methods on QAP generation are based on handcrafted features or neural networks. While they have met with certain success from different perspectives, the grand challenge of generating adequate QAPs still remains.

We present a new approach to tackling this challenge. In particular, we use a sequence of vectors to represent a sentence, where each vector consists of a semantic-role (SR) tag, a part-of-speech (POS) tag, and other syntactic and semantic tags, and we refer to such a sequence as a meta sequence. We then present a scheme called MetaQA to learn meta sequences of declarative sentences and the corresponding interrogative sentences from a training dataset. Combining and removing redundant meta sequences yields a set called MSDIP (Meta-Sequence-Declarative-Interrogative Pairs), with each element being a pair of an MD and corresponding MI(s), where MD and MI stand for, respectively, a meta sequence for a declarative sentence and for an interrogative sentence. A trained MetaQA model generates QAPs for a given declarative sentence $s$ as follows: Generate a meta sequence for $s$, find a best-matched MD from MSDIP, generates meta sequences for interrogative sentences according to the corresponding MIs and the meta sequence of $s$, identifies the meta-sequence answer to each MI, and coverts them back to text to form a QAP.
We implement MetaQA for the English language using SR, POS, and NE (named-entity) tags. We then train MetaQA using a moderate initial dataset and show that MetaQA generates efficiently a large number of adequate QAPs with an accuracy of 97% on the official SAT practice reading tests. These tests contain a large number of declarative sentences in different patterns, and there is no match in the initial MSDIP for some of these sentences. After learning interrogative for some of these sentences, MetaQA successfully generate many more adequate QAPs.

The rest of the paper is organized as follows: We describe in Section 2 related work, in Section 3 the details of meta sequence learning. We then present in Section 4 the answer generation. We report evaluation results in Section 5. Finally, we conclude the paper in Section 6.

2 Related Work

Automatic question generation (QG), first studied by Wolfe (Wolfe, 1976) as a means to aid independent study, has since attracted increasing attentions in two lines of methodologies: transformative and generative.

Transformative methods.  Transformative methods transform key phrases from a given single declarative sentence into factual questions. Existing methods are rule-based on syntax, semantics, or templates.

Syntactic-based methods follow the same basic strategy: Parse sentences using a syntactic parser to identify key phrases and transform a sentence to a question based on syntactic rules. These include methods to identify key phrases from input sentences and use syntactic rules for different types of questions (Varga and Ha, 2010), generate questions and answers using a syntactic parser, a POS tagger, and an NE analyzer (Ali et al., 2010), transform a sentence into a set of questions using a series of domain-independent rules (Danon and Last, 2017), and generate questions using relative pronouns and adverbs from complex English sentences (Khullar et al., 2018).

Semantic-based methods create questions using predicate-argument structures and semantic roles (Mannem et al., 2010), semantic pattern recognition (Mazidi and Nielsen, 2014), subtopics based on Latent Dirichlet Allocation (Chali and Hasan, 2015), or semantic-role labeling (Flor and Riordan, 2018). These methods are similar. The only difference is that semantic-based methods use semantic parsing while syntactic-based methods use syntactic parsing to determine which specific words or phrases should be asked. In a language with many syntactic and semantic exceptions, such as English, these methods would require substantial manual labor to construct rules.

Template-based methods are for special-purpose applications with built-in templates. Research in this line devises a Natural Language Generation Markup Language (NLGML) (Cai et al., 2006); uses a phrase structure parser to parse text and construct questions using enhanced XML (Rus et al., 2007); devise a self-questioning strategy to help children generate questions from narrative fiction (Mostow and Chen, 2009); use informational text to enhance the self-questioning strategy (Chen, 2009); apply pattern matching, variables, and templates to transform source sentences into questions similar to NLGML (Wyse and Piwek, 2009); defines a question template as pre-defined text with placeholder variables to be replaced with content from the source text (Lindberg, 2013); or incorporates semantic-based methods into a template-based method to support online learning (Lindberg et al., 2013).

Generative methods.  Recent advancements of neural-network methodologies have shed new light on generative methods. For example, the attention mechanism (Luong et al., 2015) is used to determine what content in a sentence should be asked, and the sequence-to-sequence (Bahdanau et al., 2014; Cho et al., 2014) and the long short-term memory (Sak et al., 2014) mechanisms are used to generate each word in a question (see, e.g., (Du et al., 2017; Duan et al., 2017; Harrison and Walker, 2018; Sachan and Xing, 2018)). These models, however, only deal with question generations without generating correct answers. Moreover, training these models require a dataset comprising over 100K questions.

To address the problem of generating questions without answers, researchers have explored ways to encode a passage (a sentence or multiple sentences) and an answer word (or a phrase) as input, and determine what questions are to be generated for a given answer (Zhou et al., 2018; Zhao et al., 2018; Song et al., 2018). Kim et al. (Kim et al., 2019) pointed out that these models could generate a number
of answer-revealing questions (namely, questions contain in them the corresponding answers). They then devised a new method by encoding answers separately, at the expense of having substantially more parameters. Their experiments show that the BLEU-4 (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), and ROUGE-L (Lin, 2004) scores on the questions generated are, respectively, 16.2, 19.92, 43.96, which are 3 to 4 points higher than the earlier results on the same dataset (Du et al., 2017). On top of low accuracy, it is also unknown whether the questions generated are grammatically correct because these measures do not measure grammatical correctness.

3 Meta Sequence Learning

Our objective is to generate adequate QAPs on a given declarative sentence written in a given language $L$. We assume that $L$ has an oracle $O_L$ to provide syntactic and semantic information on a given sentence.

1. $O_L$ can distinguish simple sentences (i.e., there is only one predicate) and complex sentences (i.e., there are two or more predicates). A complex sentence has two kinds: The first kind consists of a simple sentence as a main clause and a few subordinate clauses (simple or complex sentences) or sentence segments with normalized verbs. The second kind consists of a few independent sentences (simple or complex) connected by conjunction.

2. $O_L$ can segment sentences into a sequence of basic units. A basic unit could be a phrasal verb, a phrasal noun, or simply a word that does not belong to any phrase (if any) contained in the sentence.

3. $O_L$ can assign each basic unit in a sentence with an SR tag and a POS tag. For a complex sentence of the first kind, $O_L$ can tag the main clause as a simple sentence and each subordinate clause with one SR tag (such as time and cause), and tag each subordinate clause itself as a sentence. For a complex sentence of the second kind, $O_L$ simply separates the sentence into a collection of individual sentences and tags them accordingly. Moreover, $O_L$ may be able to produce other semantic or syntactic tags for each basic unit.

4. $O_L$ can identify an interrogative pronoun by a POS tag. An interrogative sentence, however, may or may not include an interrogative pronoun.

For example, exiting NLP tools for the English language provide a reasonable approximation to such an oracle. Better approximations are expected when more NLP techniques are developed.

Definition 1 Let $k \geq 2$ be a number of tags that $O_L$ can assign to a basic unit. A $k$-semantic-syntactic unit ($k$-SSU) is a $k$-dimensional vector of tags, denoted by $(t_1, t_2, \ldots, t_k)$, where $t_1$ is an SR tag, $t_2$ is a POS tag, and $t_i (i > 2)$ represent other tags of fixed types.

For example, we may add an NE tag to a basic unit to form a 3-SSU; adding one more tag on sentiment forms a 4-SSU. Let $U = (t_1, t_2, \ldots, t_k)$ be an SSU. Denote by $U.i = t_i (i \geq 1)$. The prefix $k$ is omitted when there is no confusion.

Two consecutive SSUs $A$ and $B$ with $A.1 = B.1$ (i.e., they have the same SR tag) and $A$ appearing on the left side of $B$ in a sentence may be merged to a new SSU $C$ as follows: (1) If $A = B$, then set $C \leftarrow A$. (2) Otherwise, based on the underlying language $L$, either set $C.2 \leftarrow A.2$ (i.e., use the POS tag on the left) or set $C.2 \leftarrow B.2$. For the rest of the tags in $C$, select a corresponding tag in $A$ or $B$ according to $L$. The following proposition is evident:

Proposition 1 For any sequence of SSUs, after merging, the new sequence of SSUs does not have two consecutive SSUs with the same SR tag.

To accommodate the situation without proper segmentation of phrasal verbs (see Section 4.5), it is desirable to allow a fixed number of consecutive SSUs to have the same SR tag in a meta sequence.

Definition 2 A meta sequence is a sequence of SSUs such that each SR tag appears at most $r$ times, with interrogative pronouns (if any) left as is without tagging, where $r \geq 1$ is a positive constant.

We assume the availability of sentence segmentation that can segment a complex sentence to form simple sentences for each clause (main and subordinate), and we treat such a sentence as a set of simple
sentences. If a clause itself is a complex sentence, it can be further segmented as a set of simple sentences. A declarative sentence consists of at least three different SR tags corresponding to subject, object, and predicate.

Since a complex sentence can be treated as a list of simple sentences, MetaQA learns meta sequences of declarative sentences and the corresponding interrogative sentences from a training dataset consisting of such pairs of sentences, where a declarative sentence is a simple sentence.

However, there are complex sentence that are not easily segmented into a set of simple sentences using the existing NLP tools. To represent this type of complex sentences, we may define a meta sequence as a recursive list of SSUs with a tree structure to represent a sentence using the notion of list in the LISP programming language. This will be addressed in a separate paper.

MetaQA consists of two phases: learning and generation. In the learning phase, MetaQA learns meta sequence pairs from an initial training dataset to generate an initial MSDIP. In the generation phase, it takes a declarative sentence as input and generates QAPs using MSDIP. Figure 1 depicts the general architecture and data flow of MetaQA, which consists of six components: Preprocessing (PP), Meta Sequence Generation (MSG), Meta Sequence Learning (MSL), Meta Sequence Matching (MSM), and QAP Generation (QAPG) (see Section 4 for detailed explanations of these components in connection to an implementation of the English language).

Both phases use the same PP and MSG components. The PP component is responsible for tagging basic units in a given sentence (declarative or interrogative) with SR tags, POS tags, and other syntactic and semantic tags, and segmenting complex sentences into a set of simple sentences using oracle $O_L$.

The MSG component is responsible for merging SSUs to form a meta sequence. Moreover, for an input sentence in the generation phase, MSG also maps each SSU after merging to the underlying text.

**Learning Phase**

The MSL component removes redundant meta sequences for each pair of MD and MI generated from MSG and stores the remaining pairs in the MSDIP database. Recall that an interrogative pronoun identified by POS tag in an MI is left as is without using its SSU.

Note that for any language, $k$ is a constant, so are the number of SR tags, the number of POS tags, and the number of other tags. The following proposition is straightforward.

**Proposition 2** (1) For a given language, the length of a meta sequence is bounded above by a constant, so is the size of MSDIP. (2) The length of a meta sequence for a declarative sentence is at least 3.

**Generation phase**

Let $M$ be a meta sequence. Denote by $M'$ the set of SSUs contained in $M$ and $|M|$ the size of $M'$. After MetaQA is trained, it generates QAPs from a given declarative sentences $s$ using the following QAP-generation algorithm, where $X_s$ is the meta sequence for $s$ generated from MSG. Recall that the text for each SSU is stored in the SSU-Text Map.
Step 1. Find a meta sequence \( MD \) \( X \) from \((MD, MI)\) pairs in MSDIP that is the best match of \( X_s \). This means that the longest common substring of \( X \) and \( X_s \), denoted by \( Z = \text{LCS}(X, X_s) \), is the longest among all MDs in MSDIP. A substring is a sub-sequence of consecutive SSUs. If \( Z \) contains SSUs for, respectively, a subject, a predicate, and an object, then we say that it is a successful match. If furthermore, \( Z = X = X_s \), then we say that it is a perfect match. If \( Z \) is missing a subject SSU, a predicate SSU, or an object SSU, then it is an unsuccessful matching. If a match is successful, got Step 2. If a match is unsuccessful or successful but not perfect, then notify the user that MetaQA needs to learn a new pattern and ask for interrogative sentences for \( s \) from the user. After this, go to Step 2.

Step 2. The goal is to generate all possible interrogative sentences for \( s \). For each pair \((X, Y)\) \( \in \) MSDIP, generate a meta sequence \( Y_s \) from \( Y \) with

\[
Y_s' = [Y' - (X' \cap Y' - X_s')] \cup (X_s' - Z').
\]

This means that \( Y_s' \) is obtained from \( Y' \) by removing SSUs that are in both meta sequences in the matched pair but not in the input sentence, and adding SSUs in the input sentence but not in the matched MD. Since \( Z = \text{LCS}(X, X_s) \), the following proposition is straightforward:

**Proposition 3** \( X_s' - Z' = X_s' - X' \).

Order SSUs in \( Y_s' \) appropriately to form \( Y_s \), which requires localization according to the underlying language. If an SSU in \( Y_s' \) has the corresponding text stored in Step 1, then replace it. If not, then it requires localization to resolve it. This generate an interrogative sentence \( Q_s \) for \( s \).

Step 3. For each interrogative sentence \( Q_s \) generated in Step 3, the SSUs in \( A_s' = X_s' - Y_s' \) represent a correct answer. Place SSUs in \( A_s' \) in the same order as in \( X_s' \) and replace each SSU with the corresponding text in \( s \) to obtain an answer \( A_s \) for \( Q_s \).

4 An Implementation of MetaQA for English

SR, POS, and NE tags are used in this implementation. Existing NLP tools for generating these tags are for words, not for phrases. We could, however, use phrase segmentation to resolve this by appropriate merging operations. While word segmentation is not needed in alphabetic languages such as English, phrase segmentation provides a better interpretation of the underlying sentence. We first assume the existence of an ideal phrase segmentation for English, and then discuss how to get around it at the end of this section.

4.1 Preliminaries

The following NLP tools are used to generate tags: Semantic-Role Labeling (SRL) \( \text{Shi and Lin, 2019} \) for SR tags, POS Tagging \( \text{Toutanova et al., 2003} \) for POS tags, and Named-Entity Recognition (NER) \( \text{Peters et al., 2017} \) for NE tags.

SR tags are defined in PropBank\(^1\) \( \text{Bonial et al., 2012} \) \( \text{Martha et al., 2005} \), which consist of three types: ArgN (arguments of predicates), ArgM (modifiers or adjuncts of the predicates), and V (predicates). ArgN consists of six tags: ARG0, ARG1, . . . , ARG5, and ArgM consist of multiple subtypes such as LOC as location, EXT as extent, DIS as discourse connectives, ADV as general purpose, NEG as negation, MOD as modal verb, CAU as cause, TMP as time, PRP as purpose, MNR as manner, GOL as goal, and DIR as direction.

POS tags\(^2\) are defined in the Penn Treebank tagset \( \text{Toutanova et al., 2003} \) \( \text{Marcus et al., 1993} \). For example, NNP is for singular proper noun, VBZ for third-person-singular-present-tense verb. DT for determiner, and IN for preposition or subordinating conjunction.

NE tags include PER for persons, ORG for organization, LOC for locations, and numeric expressions for time, date, money, and percentage.

\(^1\)https://verbs.colorado.edu/mpalmer/projects/ace/EPB-annotation-guidelines.pdf

\(^2\)https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html
4.2 PP, MSG, and MSL Localization

The PP, MSG, and MSL components, on top of what is described in Section 3, incur the following localization. PP first replaces contractions and slang with words or phrases to help improve tagging accuracy. For example, contractions 'm, 's, 're, 've, n’t, e.g., i.e., a.k.a. are replaced by, respectively, am, is, are, have, not, for example, that is, also known as. Slang gonna, wanna, gotta, gimme, lemme, ya are replaced by, respectively, going to, want to, got to, give me, let me, you.

PP then segments sentences and tags words in sentences using SRL, POS Tagging, and NER for the training dataset and later for input sentences for generating QAPs. Use SRL to segment a complex sentence into a set of simple sentences and discard all simple sentences without a subject or an object. Note that there are complex sentences that are hard to segment using SRL. Moreover, for each sentence, PP removes all the words with a CC (coordinating conjunction) as POS tag before its subject, including and, but, for, or, plus, so, therefore, and because.

MSG then merges the remaining SSUs if two consecutive SSUs are identical. If they are not identical but have the same SR tag, then use this SR tag in the merged SSU, and the POS tag in the first SSU from the right. If they contain a noun, use the first SSU from the right with a noun POS tag. Moreover, the NE tag in the merged SSU is null if both SSUs contain a null NE tag; otherwise, use the first non-empty NE tag from the right.

4.3 MSM Localization

The MSM component takes a meta sequence $X_s$ of a sentence $s$ as input and executes Step 1 in the QAP-generation algorithm described in Section 3 using Ukkone’s Suffix-Tree algorithm (Ukkonen, 1985) to compute a longest common substring of two meta sequences, which runs in linear time. During matching, the POS tags for various types of nouns are treated equal; they are NN, NNP, NNS, and NNPS. The POS tags for third-person-singular-present verbs are treated equal; they are VBP and VBZ. To use Ukkone’s algorithm, we encode a meta sequence as a sequence of symbols using / to separate tags in an SSU. That is, vector $(t_1, t_2, t_3)$ is now written as $t_1/t_2/t_3$. If $t_2$ is null, then write it as $t_1//t_3$. If $t_3$ is null, then write it as $t_1/t_2//$. If both are null, then write it as $t_1//$. SSUs in a sequence are just written as concatenation. For example, the sentence “Abraham Lincoln the 16th president of the United States” has the following SSUs:

Abraham (ARG1/NNP/PER) Lincoln (ARG1/NNP/PER) was (V/VBZ/) the (ARG2/DT/) 16th (ARG2/JJ/) president (ARG2/NN/) of (ARG2/IN/) the (ARG2/DT/) United (ARG2/NNP/LOC) States (ARG2/NNP/LOC).

The meta sequence for this sentence is, after merging: ARG1/NNP/PER V/VBZ/ ARG2/NNP/LOC.

Let $X$ be an MD in MSDIP such that LCS($X, X_s$) is the longest among all MDs in MDDIP, denoted by $Z$.

4.4 QAPG Localization

The QAPG component executes Steps 2–3 in the QAP-generation algorithm described in Section 3. Recall that $Z = LCS(X, X_s)$ is the longest match among all MDs in MSDIP, and after the set of SSUs $Y'_s$ is generated, localization is needed to form $Y_s$.

Case 1: $Z = X_s$. Then $Y_s = Y$.

Case 2: $Z$ is a proper substring of $X_s$. Then each SSU in $X'_s - Z$ appears either before $Z$ or after $Z$. Form a string $Y_a$ and $Y_b$ of the SSUs that appear, respectively, before and after $Z$ in the same order as they appear in $X_s$. Let $Y_s = [Y - (X' \cap Y' - X'_s)]Y_aY_b$, where $Y - (X' \cap Y' - X'_s)$ means to remove from $Y$ the SSUs in $X' \cap Y' - X'_s$.

For each SSU in $Y_s$ if a corresponding text can be found in the SSU-Text Map, then replace it with the text. An SSU that doesn’t have a matched text in the SSU-Text Map is due to the helping verbs added in the interrogative sentence that generates $Y$. There are five POS tags for verbs: VBG for gerund or present participle, VBD past tense, VBN past participle, VBP non-3rd person singular present, and VBZ 3rd person singular present. Present participle and past participle have already included helping verbs,
and so do the negative forms of past tense and present tense. Thus, only positive forms of past tense (VBD) and present tense (VBP, VBZ) do not include helping verbs, which need to be resolved.

**Rule for resolving helping verbs**

The first V-SSU in Y (i.e., the SSU that contains the SR tag of V) is a helping verb. To determine its form, check the POS tag in the subject SSU (usually it is ARG0) and determine if it is singular or plural. Then check the POS tag in the first V-SSU in Y to determine the tense. Replace the second V-SSU with the verb in its original form for the V-SSU in the SSU-Text MAP.

For example, suppose that the following declarative sentence “John traveled to Boston last week” and its interrogative sentence about location “Where did John travel to last week” are in the training dataset, which generate the following SSUs before merging:

- John (ARG0/NNP/PER) traveled (V/VBD/) to (ARG1/IN/) Boston (ARG1/NNP/LOC) last (TMP/NN/) week (TMP/NN/).
- Where (Where) did (V/VBD/) John (ARG0/NNP/PER) travel (V/VB/) to (ARG1/IN/) last week (TMP/NN/)?

Since “travel to” is a phrasal verb, after merging, we have

- John (ARG0/NNP/PER) traveled to (V/VBD/) Boston (ARG1/NNP/LOC) last week (TMP/NN/).
- Where (Where) did (V/VBD/) John (ARG0/NNP/PER) travel to (V/VB/) last week (TMP/NN/)?

The following meta-sequence pair \((X, Y)\) is learned for MSDIP:

\(X = \text{ARG0/NNP/PER V/VBD/ ARG1/NNP/LOC TMP/NN/} \)
\(Y = \text{Where V/VBD/ ARG0/NNP/PER V/VB/ TMP/NN/} \)

Suppose that we are given a sentence \(s = \text{“Mary flew to London last month.”}\) Its meta sequence \(X_s\) is exactly the same as \(X\), with ARG0/NNP/PER for “Mary”, V/VBD for “flew to”, ARG1/NNP/LOC for “London”, and TMP/NN for “last month”, which are stored in the SSU-Text Map. Thus, \(Y_s = Y\).

We can see that the SSU of V/VB in \(Y\) is not in the SSU-Text Map. To resolve the unmatched V/VB, check the POS tag in the ARG0-SSU, which is NNP, indicating a singular noun. The POS tag in the first V-SSU is VBD, indicating past tense. Thus, the correct form of the helping verb is “did”. The text for V/VBD is “flew to” in the SSU-Text Map. The original form of the verb is “fly”. Thus, the second V-SSU is replaced with “fly”. This generates the following interrogative sentence: “Where did Mary fly to last month?” The answer SSU is \(X' - Y'\), which is ARG1/NNP/LOC, corresponding to “London”.

### 4.5 SSU Merging without Segmentation

To the best of our knowledge, no tools exist at this point that can segment English sentences to identify phrasal nouns and phrasal verbs. It is worth mentioning that AutoPhrase (Shang et al., 2018) can be used for identifying certain phrasal nouns. We could deal with phrasal verbs using a list of common phrasal verbs or by modifying merging operations. A phrasal verb consists of a preposition or an adverb, or both. There are four POS tags IN for preposition or subordinating conjunction, RB for adverb, RBR for comparative adverb, and RBS for superlative adverb.

To see this problem, let us look at the same example aforementioned. After merging, we have

- John (ARG0/NNP/PER) traveled (V/VBD/) to Boston (ARG1/NNP/LOC) last week (TMP/NN/).
- Where (Where) did (V/VBD/) John (ARG0/NNP/PER) travel (V/VB/) to (ARG1/IN/) last week (TMP/NN/)?

For the input sentence we have

- Mary (ARG0/NNP/PER) flew (V/VBD/) to London (ARG1/NNP/LOC) last month (TMP/NN/).

The interrogative sentence is “Where did Mary fly ARG1/IN/ last week?” after replacing SSUs with text in the SSU-Text Map, with ARG1/IN/ unmatched with text. We can resolve this by modifying the merging operation as follows: When an SSU with a POS tag for preposition or adverb appears appears before or after a V-SSU, leave it as is without merging it with its neighboring SSUs of the same SR tag, unless the POS tags in them are also for prepositions or adverbs. The rest of the merging operations are the same. Then we have, after merging,

- John (ARG0/NNP/PER) traveled (V/VBD/) to (ARG1/IN/) Boston (ARG1/NNP/LOC) last week (TMP/NN/).
Where (Where) did (V/VBD/) John (ARG0/NNP/PER) travel (V/VB/) to (ARG1/IN/) last week (TMP/NN/)?

Now the input sentence becomes, after SSU merging,

Mary (ARG0/NNP/PWR) flew (V/VBD) to (ARG1/IN/) London (ARG1/NNP/LOC) last moth (TMP/NN/).

All the SSUs in the meta sequence “Where V/VBD/ ARG0/NNP/PER V/VB/ ARG1/IN/ TMP/NN/” have corresponding text in the SSU-Text Map after resolving for helping verbs. The answer SSU is in \(X' - Y' = \text{ARG1/NNP/LOC}\), which is “London”.

5 Evaluations

To evaluate MetaQA, we need to have appropriate evaluation measures, training data, and evaluation data. BLUE (Papineni et al., 2002), ROUGE (Lin, 2004), and Meteor (Lavie and Denkowski, 2009) are standard evaluation metrics for measuring automatic summarization and machine translation, which are good for computing text similarity and have also been used to evaluate QG. Another commonly-used measure is human judgments. BLEU and ROUGE-N count the number of overlapping units between the candidate text and the reference text by using N-grams. ROUGE-L measures the cognateness between the candidate text and the reference text by using Longest common sub-sequence. Meteor compares the candidate text with the reference text in terms of exact, stem, synonym, and paraphrase matches between words and phrases. These metrics, however, do not evaluate grammatical correctness. Thus, human judgment is the only liable measure for grammatical correctness.

SQuAD (Rajpurkar et al., 2016) is a dataset that has been used for training and evaluating generative methods for QG. However, not all QAPs in SQuAD are well-formed or with correct answers. There are also about 20% of questions in the dataset that require paragraph-level information. Thus, SQuAD is unsuitable for evaluating QAPs for our purpose. Instead, we constructed an initial training dataset by writing a number of declarative sentences and the corresponding interrogative sentences to cover the major tense, participles, voice, modal verbs, and some common phrasal verbs such as “be going to” and “be about to” for the following six interrogative pronouns: Where, Who, What, When, Why, How many. A total of 112 meta-sequence pairs (MD, MI) were learned as the initial MSDIP.

To evaluate MetaQA, we extracted declarative sentences from the official SAT practice reading tests\(^3\), for the reason that SAT practice reading tests provide a large number of different patterns of declarative sentences. There are a total of eight SAT practice reading tests, each consisting of five articles and each article consisting of around 25 sentences, for a total of 40 articles and 1,136 sentences. After removing easy-to-identify interrogative sentences and imperative sentences, we harvested a total of 1,025 sentences (which may still contain imperative sentences). Using the initial MSDIP, MetaQA generated a total of 796 QAPs.

Three native Chinese speakers evaluated the QAPs on a shared Google doc file based on the following criteria: For questions: Check both syntax and semantics: (1) correct; (2) acceptable (e.g., a minor would make it correct); (3) not acceptable. For answers: (1) matched—the answer matches well with the question; (2) acceptable; (3) not acceptable. The final results were agreed by the three judges. Presented below are questions generated with detailed breakdowns in each category, where “all correct” means both syntactically and semantically correct and conforming to native-speaker norms, “not acceptable” means either syntactically or semantically unacceptable, and “How” means “How many”:

|              | Where | Who | What | When | Why | How | Total |
|--------------|-------|-----|------|------|-----|-----|-------|
| MSDIP pairs  | 18    | 45  | 23   | 22   | 6   | 8   | 122   |
| QAPs generated | 26   | 216 | 466  | 51   | 15  | 22  | 796   |
| All correct  | 21    | 208 | 458  | 51   | 15  | 20  | 773   |
| Syntactically acceptable | 4    | 4   | 3    | 0    | 0   | 2   | 13    |
| Semantically acceptable | 1    | 2   | 5    | 0    | 0   | 0   | 8     |
| Not acceptable | 0    | 2   | 0    | 0    | 0   | 0   | 2     |

\(^3\)https://collegereadiness.collegeboard.org/sat/practice/full-length-practice-tests
The percentage of generated questions that are both syntactically and semantically correct is 97%. We noticed that there is a strong correlation between the correctness of the questions and their answers. In particular, when a generated question is all correct, its answer is also all correct. When a question is acceptable, its answer may be all correct or acceptable. Only when a question is unacceptable, its answer is also unacceptable.

The 13 incorrect but syntactically acceptable questions are mostly due to some minor issues in segmenting a complex sentence into simple sentences, where a better handling of sentence segmentation is expected to correct these issues. Two questions whose interrogative pronoun should be “how much” are mistakenly using “how many”. Further refinement of POS tagging that distinguish uncountable nouns from countable nouns would solve this problem. The eight semantically acceptable questions are all due to NE tags that cannot distinguish between persons, location, and things. Further refinement of NE tagging will solve this problem. The two unacceptable questions are due to serious errors induced when segmenting complex sentences. This suggests that we should look into using a recursive list to represent complex sentences.

There were 589 sentences for which no matched meta sequences are found from the initial MSDIP. By learning new meta sequences from user inputs, 535 of these sentences found perfect matching, which generate QAPs that are both syntactically and semantically correct. For the remaining 84 sentences, some are imperative sentences without a clear structure of subject-predicate-object, and some are hard to segment into a set of simple sentences due to inaccurate SR tagging and so no appropriate (MD, MI) pairs were learned. This suggests that we should look into better sentence segmentation methods or meta trees as recursive lists of meta sequences to represent complex sentences as a whole, which is left for future work.

We evaluated the running time to generate QAPs over 100 sentences on a desktop computer with an Intel Core I5 2.6 Ghz CPU and 16 GB RAM. The average running time is 0.55 seconds for each input sentence, which is deemed satisfactory for online applications. For a given article, assuming that it would take the reader several minutes to read. By then all the QAPs for MCQs would have been generated.

6 Conclusions and Final Remarks

Meta sequence learning is a novel approach for generating adequate QAPs, which achieves satisfactory results for the English language using existing NLP tools on SR, POS, and NE tagging. Further improvement of named-entity recognition may be able to eliminate a small number of semantic errors we encountered in our evaluations. When almost all possible patterns of declarative sentences and the corresponding interrogative sentences are learned (there are only finitely many of them to be learned), MetaQA is expected to perform well on generating adequate QAPs from declarative sentences that can be segmented appropriately into simple sentences.

However, not all complex sentences can be segmented using existing tools. In particular, about 7.4% of the declarative sentences in the official SAT practice reading tests are in this category. This calls for, as mentioned near the end of Section 5, a better NLP method to help dissect complex sentences. Another approach to resolving this is to use a tree structure of meta sequences. For example, we may be able to represent a complex sentence as a recursive list of meta sequences.

Applying MetaQA to a logographic languages would require robust and accurate segmentation at all levels of words, phrases, and sentences, semantic labeling, POS tagging, and named-entity recognition for the underlying languages. It would also require appropriate localization for merging SSUs. It is interesting to explore how well MetaQA performs on a language other than English.

Generating QAPs on derived points remains a challenge. It calls for a major breakthrough in machine inference. It would be interesting to investigate how meta sequence learning may help generate such QAPs. Incorporating neural-network technologies and meta sequence learning could be a direction worth exploring. Adding more semantic tags and syntactic tags may also help, such as sentiment tags and logic tags to carry out certain forms of reasoning.
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