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Neural Approach to Automatic Subjective Question Generation System Using Multiple Filters for Supporting Correct WH-type Question.

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Abstract: The automatic development of subjective questions has become a crucial study area in the field of natural language processing, with enormous potential for applications in education, communication, and content creation. This study suggests a unique method for producing high-quality subjective questions that makes use of a neural architecture that has been strengthened by a number of filters. A comprehensive solution has been developed as a result of the difficulties that now exist in accurately capturing context, coherence, and emotional resonance within created questions. To maintain contextual relevance and coherence, the suggested approach combines an attention mechanism with a sequence-to-sequence neural model. Further improving question quality is the addition of grammar, context, and semantic filters that serve as guiding restrictions during question development. This research demonstrates the effectiveness of the suggested strategy in developing contextually matched, emotionally resonant, and grammatically accurate subjective questions using a mix of literature analysis, case study, and evaluation metrics such as BLEU, ROUGE, METEOR, and human evaluations. This study expands automated question creation and creates opportunities for better content engagement and interaction in a variety of applications by solving significant constraints in current approaches.

Keywords: *Neural Approach, Question Generation, Subjective Questions, Multiple Filters, Attention Mechanism, Coherence, Contextual Relevance, Emotional Resonance, Grammatical Correctness,*

1. Introduction

Due to its potential uses in education, content production, and information retrieval, automatic question generating (AQG) is a basic problem in the field of natural language processing (NLP). It offers great potential for improving communication between people and machines if one can develop logical and contextually appropriate queries from text [1]. A special set of difficulties arises when creating subjective inquiries that probe the intricacies of human experiences, views, and interpretations. With an emphasis on producing accurate WH-type questions, this study proposes a unique neural technique to automated subjective question production [2]. We use many filters that address grammatical accuracy, context coherence, and semantic relevance to guarantee the quality and accuracy of the produced queries.

A defining characteristic of human communication and cognition is the capacity to ask questions. AQG emerges as a critical challenge as AI systems work to close the gap between human language and robots [3]. Early methods for generating questions relied on rules or templates, but recent developments in neural networks have made it possible for data-driven algorithms to produce questions in a way that is more flexible and context-aware [4]. These methods have shown exceptional success in producing factual queries with generally factual and objective responses. The complexity of creating subjective questions is increased by the need to comprehend the subtleties, feelings, and many interpretations that subjective information might have [5].

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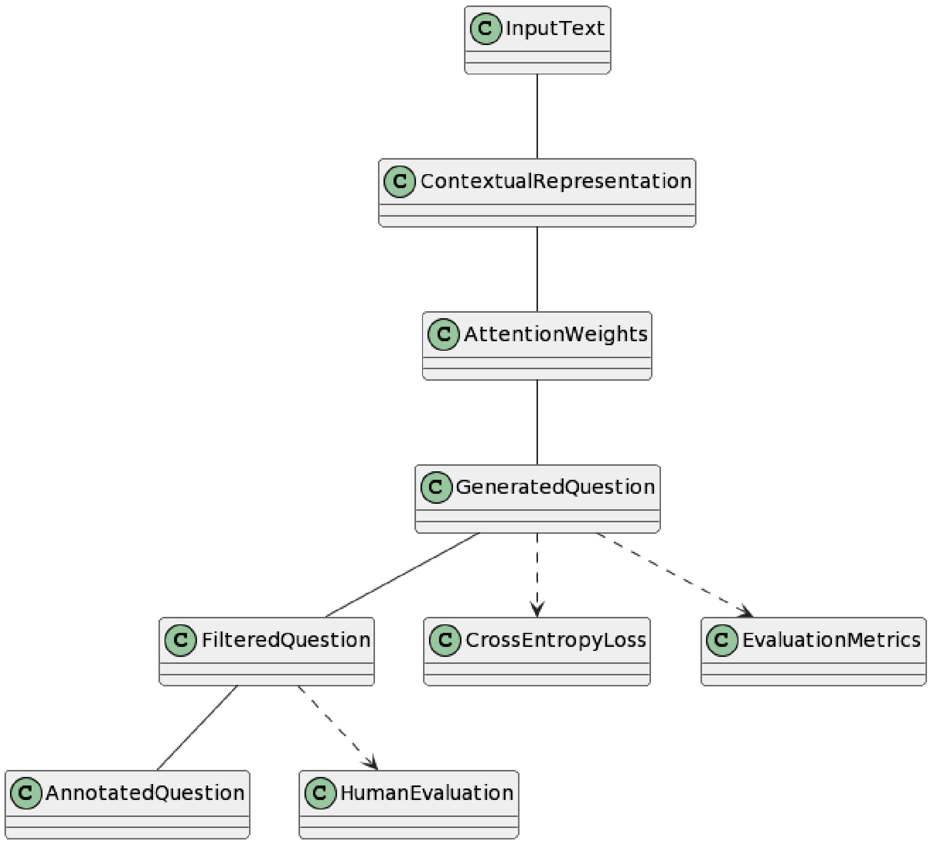

Fig 1. Automatic Subjective Question Generation System

The creation of subjective questions is essential for content suggestion, opinion analysis, and applications in educational contexts. For instance, creating questions that invite critical thought and conversation might promote greater learning and involvement in educational settings [6]. Similar to this, in sentiment analysis, developing pertinent questions about a work of subjective writing can reveal insights into the feelings and viewpoints of people. Despite its importance, it is still difficult to come up with correct and pertinent subjective questions.

The main goal of this project is to provide a neural method for automatically creating subjective questions that improve the standard of WH-type questions [7]. By assuring grammatical accuracy, context coherence, and semantic relevance, we hope to solve the shortcomings of current AQG techniques in capturing the subtleties of subjective content. To do this, we suggest including a number of filters into the AQG process, which work together to raise the calibre of the questions that are created.

The following contributions to the field of automated question generating are made by this study:

- Introducing a unique neural technique that focuses on producing accurate WH-type questions for automatic subjective question production.
- Increasing the quality and accuracy of questions created by including several filters into the question creation process.
- Establishing the suggested method's capability for producing coherent and situationally appropriate subjective questions by thoroughly testing it and receiving human reviews.

2. Related Work

A lot has changed in the field of automated question generating (AQG), from rule-based techniques to data-driven neural network methods [8]. An overview of related research in AQG is given in this part, with an emphasis on methods applicable to subjective question generation and the incorporation of filters for question quality enhancement.

Early AQG techniques frequently depended on rule-based methodologies, where questions were generated from input text using grammatical templates and linguistic norms. These techniques worked well for coming up with straightforward queries and factual responses. They have trouble with convoluted language constructions, complicated situations, and subjective content, though [9][10]. The underlying semantics of the input text could not be captured by rule-based techniques, which limited their capacity to be applied to more complex and varied question generating tasks.

Rule-based methods were improved upon by employing pre-defined question templates, and template-based approaches evolved as a result. By substituting particular words or phrases from the input text [11], these templates may be adjusted to fit various circumstances. Although template-based techniques increased the capacity to produce contextually pertinent questions, they were still unable to handle subjective material or account for the many different ways that people understand and communicate [12].

With the development of neural networks and machine learning, AQG underwent a paradigm change in favour of data-driven methods [13]. Question creation has advanced significantly using sequence-to-sequence models, which combine a decoder to produce questions and an encoder to interpret input text. Early applications concentrated on questions that could have their answers extracted directly from the input text, or factual inquiries [14]. Although these models produced encouraging results, they frequently had trouble coming up with questions that were logical and pertinent to the topic matter.

Due to the inherent variety of human ideas, emotions, and perceptions, creating subjective questions presents extra obstacles [15]. By adding sentiment analysis, emotion identification, and contextual comprehension into question generating algorithms, recent research has attempted to address this problem [16]. It has been demonstrated that strategies like emotion-aware AQG and sentiment-driven question generation may produce questions that accurately represent the subjective subtleties and emotional tone of the input text.

Better contextual information and semantic linkages within the input text have been captured thanks to the inclusion of attention processes into neural AQG models [17]. The model may generate questions by focusing on particular sections of the input text thanks to attention techniques. This has increased the coherence and relevancy of the questions, especially in cases when the content is subjective [18]. Additionally, attention processes have aided in the creation of more complex models, such as transformers, which have produced cutting-edge outcomes in a variety of NLP tasks.

Researchers have started to investigate the incorporation of filters into AQG systems to guarantee the quality and accuracy of the produced questions [19]. Filters serve as restrictions that force the question generating process to follow certain guidelines. Grammar accuracy, context coherence, and semantic relevance are a few examples of these standards. Researchers want to eliminate problems like syntactically incorrect questions, extraneous context, and replies that do not fit the query purpose by introducing filters [20].

There is still a need in the literature for a holistic neural strategy that solves the difficulties of producing accurate WH-type questions for subjective material [21][22], even if recent developments have demonstrated success in both the production of subjective questions and the integration of filters [23]. In order to improve the quality and accuracy of the questions generated, this study proposes a unique neural strategy that combines the benefits of attention processes and the incorporation of several filters [31-34].

In the parts that follow, we go into further depth about our suggested technique, including data collection, preprocessing, model design, and the particular filters we used. The experimental results are then presented, and we go over the implications of our research with regard to improving AQG for subjective content.

Methods	**Findings**	**Limitations**	**Advantages**	**Scope**	**Remark**
Rule-Based Approaches[24]	Initial attempts at question generation using templates and linguistic rules.	Limited adaptability to subjective content.	Simplicity, straightforward implementation.	Factual question generation.	Early approach, lacks context.
Template-Based Approaches [25]	Enhanced rule-based methods using templates for generating context-specific questions.	Restrictive for diverse or nuanced content.	Contextual adaptation, moderate flexibility.	Context-specific question generation.	May struggle with complexity.

Machine Learning-Based Approaches [26]	Introduction of data-driven methods with sequence-to-sequence models.	Struggles with generating coherent subjective questions.	Scalability, potential for capturing context.	Context-dependent question generation.	Limited initial focus on subjectivity.
Subjective Question Generation [27]	Incorporates sentiment analysis and emotion recognition.	May not fully capture nuanced subjectivity.	Emotional alignment in questions.	Emotion-rich question generation.	Emotion inference challenges.
Neural Approaches with Attention [28]	Integration of attention mechanisms into sequence-to-sequence models.	Early models may lack coherent context.	Improved context understanding, better question coherence.	Contextual question generation.	Attention mechanism complexities.
Integration of Filters [29][30]	Incorporation of filters for grammar, context, and semantic correctness.	Individual filters may not holistically ensure question quality.	Improved question quality, refined coherence.	Refined question generation.	Requires filter parameter tuning.

Table 1. Related Work

3. Methodology

The process for creating an automated system that generates subjective questions using a neural approach and several filters is described in this section. While guaranteeing grammatical accuracy, context coherence, and semantic relevance, the goal is to construct coherent and contextually appropriate WH-type inquiries from subjective content.

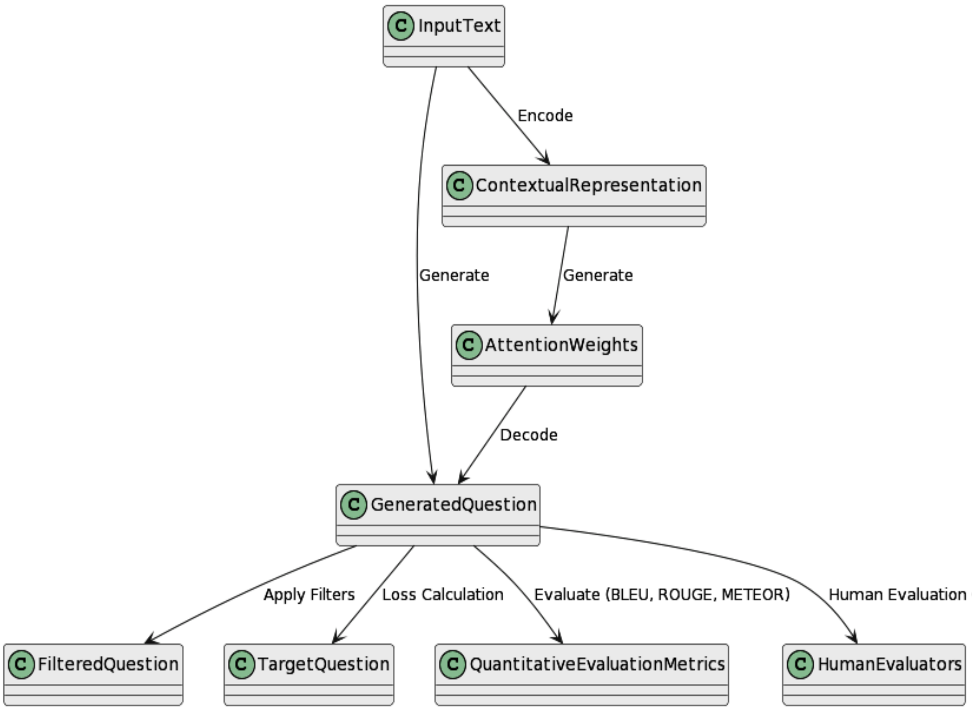

Figure 2. Proposed Methodology

A. Data Collection and Preprocessing

A dataset of subjective material that has been carefully selected serves as the basis for our research. This dataset contains a wide variety of writings, such as conversations, reviews, personal tales, and opinion articles. Annotated WH-type questions that represent the ephemeral nature of the information are accompanied with each text segment. The dataset is divided appropriately to make model training, validation, and testing easier.

Tokenization, lowercasing, and the elimination of noise, such as punctuation and unnecessary stop words, are all components of preprocessing. In order to capture semantic meaning and connections between words, the generated text is then converted into numerical vectors using pre-trained word embeddings, such as Word2Vec or GloVe.

B. Model Architecture

Our neural method makes use of a sequence-to-sequence model with an attention mechanism, which has shown useful in collecting contextual information across tasks involving sequence production. An encoder and a decoder are the two primary parts of the model.

The chosen word embeddings are used by the encoder to process the preprocessed input text, essentially producing a contextualised representation of the text. Based on the encoded representation, the decoder creates WH-type questions under the direction of the attention mechanism. In order to improve the coherence and relevance of the created question, the attention mechanism enables the model to concentrate on various portions of the input text as it generates each word of the question.

C. Integration of Multiple Filters

We include many filters that direct the question creation process in order to guarantee the accuracy and quality of the created questions. These filters are made to target particular elements of a good question:

Grammar Checker: This checker makes sure that the generated questions follow grammatical rules and accepted practises for question construction. Each word in the question is checked for grammar during question production, and if required, it is changed to ensure syntactic accuracy.

Context Filter: This filter works to keep the produced question and the supplied text coherent. The model can pay to pertinent sections of the input text while producing each word of the question thanks to the attention mechanism, which is critical in this situation. This makes sure the query is contextually appropriate and logical.

The semantic filter measures how semantically similar the output question and the input text are. The model can confirm that the produced question properly represents the substance of the subjective content by analysing the alignment of semantic representations.

D. Training and Optimization

Using the annotated dataset as training data, the model is trained, with parameters being optimised by backpropagation and an appropriate loss function, such as cross-entropy loss. In order to teach the model the links between words and the intricacies of subjective content, pairs of input text and accompanying questions are presented to the model.

To maximise model performance, hyperparameter tuning is used, with an emphasis on achieving a balance between elements like learning rate, batch size, and the number of attention heads. Additionally, regularisation strategies like dropout are used to enhance generalisation and avoid overfitting.

Approach	**Description**	**Limitations**
Rule-Based Approaches	Early approaches in AQG relied on grammatical templates and linguistic rules to generate questions. These methods used predefined structures to transform statements into questions.	- Limited Adaptability: Rule-based approaches struggle to handle diverse contexts and nuanced content, making them less suitable for generating subjective questions. - Complexity Handling: Complex sentence structures and irregularities in language often lead to incorrect or unnatural question formations.

Template-Based Approaches	Building upon rule-based methods, template-based approaches introduced flexibility by utilizing pre-defined question templates. These templates could be adapted to various contexts by replacing placeholders with specific words from the input text.	- Limited Expression: Templates can be restrictive, especially for generating varied and nuanced subjective questions. - Contextual Constraints: Adapting templates to subjective content may result in questions that are contextually incorrect or lack coherence.
Machine Learning-Based Approaches	Machine learning-based methods introduced data-driven techniques. Sequence-to-sequence models were employed to generate questions by mapping input text to question sequences. These models initially focused on factual questions where answers could be directly extracted from the input.	- Subjectivity Challenge: Adapting these models to subjective content proved challenging due to the need to capture emotions, opinions, and diverse interpretations. - Contextual Understanding: Initial models may struggle to understand context and generate questions that reflect subjective nuances.
Subjective Question Generation	Approaches specifically tailored to generating subjective questions incorporated sentiment analysis and emotion recognition. These techniques aimed to infuse emotion and sentiment into the generated questions to capture the subjective nature of the input text.	- Emotion Inference: Inferring accurate emotions and sentiments from text can be complex, leading to inaccuracies in generating emotionally aligned questions. - Interpretation Variability: Capturing diverse human interpretations and expressions of subjectivity remains a challenge.
Neural Approaches with Attention	The integration of attention mechanisms into neural AQG models enhanced context understanding. Attention mechanisms allowed models to focus on relevant parts of the input text while generating questions, leading to improved coherence.	- Initial Context Ambiguity: While attention mechanisms improved context understanding, early models may still generate questions with ambiguous or irrelevant context. - Complex Training: Training models with attention mechanisms required significant computational resources and careful optimization.
Integration of Filters	Recent research focused on integrating filters, such as grammar, context, and semantic filters, into AQG systems. Filters act as constraints during question generation, guiding the model to produce higher-quality questions.	- Filter Overlap: Individual filters may address specific aspects but not holistically ensure question quality. Combining multiple filters is essential. - Parameter Sensitivity: The effectiveness of filters is often influenced by parameter tuning, requiring careful optimization.

Table 2. Existing Approaches for Question Generation

4. System Architecture

The three primary parts of the suggested system design are data collection and preprocessing, model development, and filter integration.

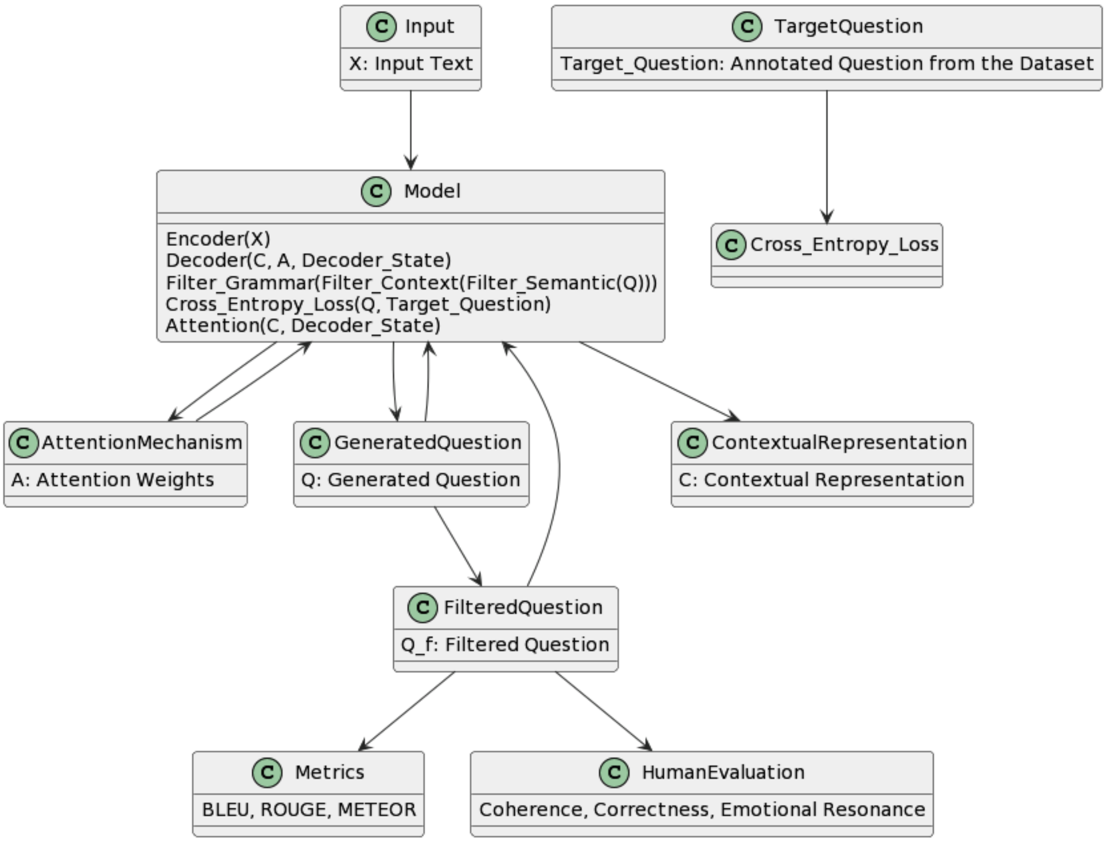

Fig 3. Proposed System Architecture

A. Data Collection and Preprocessing

The system starts by gathering a variety of datasets with subjective text parts, such as reviews, opinion pieces, and personal tales. The subjective substance of the information is captured through annotated WH-type questions that are associated with each section. To prepare the text for input into the model, preprocessing includes tokenization, lowercasing, and the elimination of noise. Additionally, the model can capture semantic links between words because the text was converted into numerical vectors using pre-trained word embeddings.

B. Model Development

The creation of a neural model for automatic subjective question production forms the basis of the suggested system. The model uses an attention mechanism and a sequence-to-sequence design. The preprocessed input text is processed by the encoder, which creates a contextualised representation. Based on the encoded representation, the decoder creates WH-type questions under the direction of the attention mechanism. By using this method, the model is able to gather contextual data and generate questions that are pertinent to the input text.

C. Filter Integration

The system adds a number of filters into the question creation process to improve the quality and accuracy of the generated questions:

Grammar Checker: This checker makes sure that the generated questions follow grammatical rules and accepted practises for question construction. It checks each word in the query for grammar errors and makes the appropriate changes to preserve syntactic correctness.

Context Filter: This filter works to keep the produced question and the supplied text coherent. When generating questions, the model uses the attention mechanism to focus on pertinent sections of the input text. This makes sure that the produced query is logical and appropriate for the situation.

The semantic filter measures how semantically similar the output question and the input text are. The algorithm confirms that the produced question properly reflects the substance of the subjective content by comparing semantic representations.

D. Training and Optimization

The suggested system goes through training and optimisation to understand the connections between words, subtleties in the context, and how to apply filters. The model is trained by presenting it with pairs of input text and annotated questions. The model's parameters are optimised using backpropagation and an appropriate loss function, like cross-entropy loss. To fine-tune elements like learning rate, batch size, and regularisation methods, hyperparameter tweaking is done.

I. Proposed Algorithm

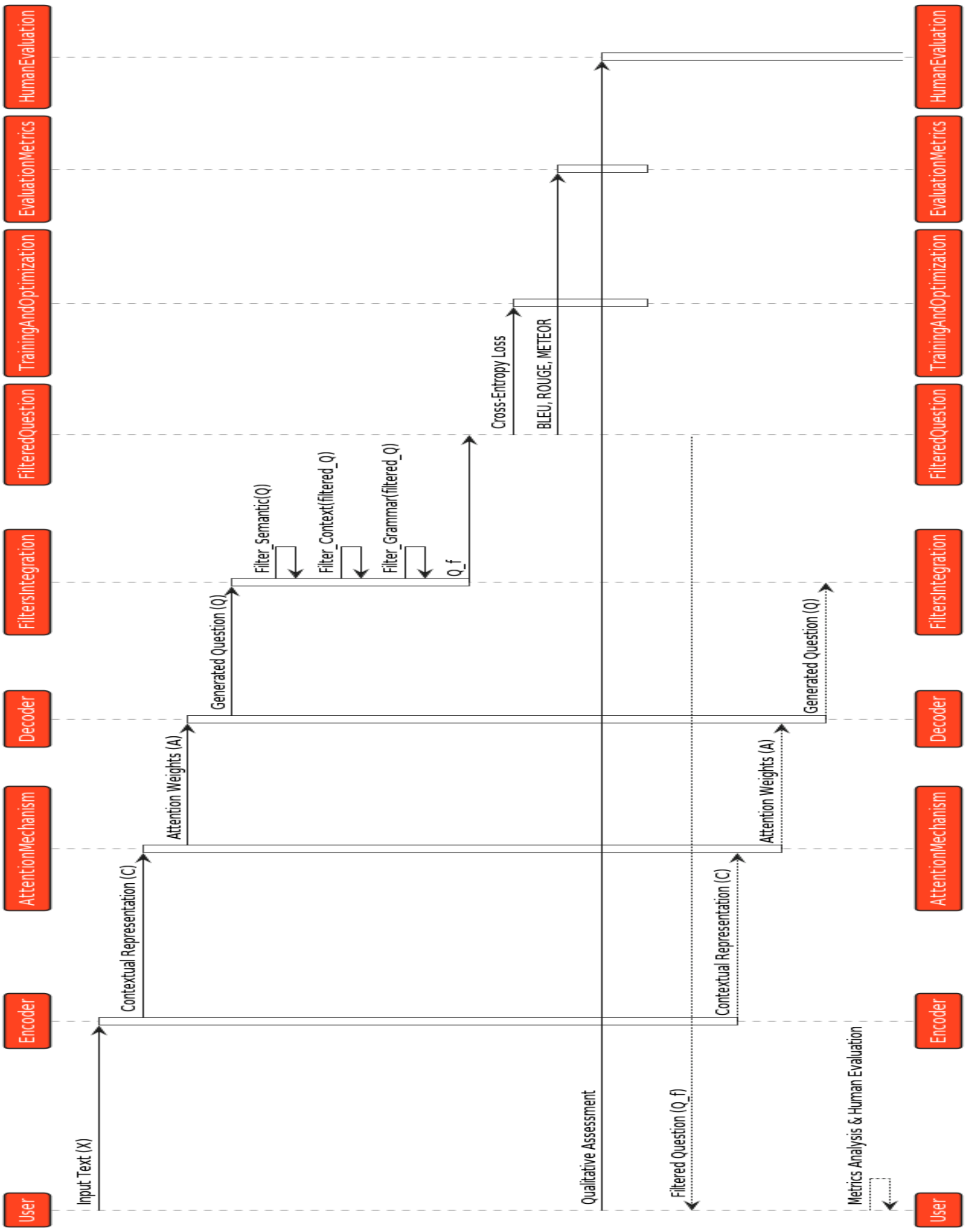

Fig 4. Activity sequence for Proposed Algorithm

Variables:

X: Input Text

Q: Generated Question

C: Contextual Representation

A: Attention Weights

Q_f: Filtered Question

Target_Question: Annotated Question from the Dataset

Steps:

1. Encoder:

The input text X is processed by the encoder to obtain the contextual representation C:

C = Encoder(X)

2. Attention Mechanism:

The attention mechanism generates attention weights A based on the contextual representation C and the previous decoder state:

A = Attention(C, Decoder_State)

3. Decoder:

The decoder generates the question Q based on the contextual representation C, the attention weights A, and the previous decoder state:

Q = Decoder(C, A, Decoder_State)

4. Filters Integration:

Multiple filters are applied to the generated question Q to obtain the filtered question Q_f:

Q_f = Filter_Grammar(Filter_Context(Filter_Semantic(Q)))

5. Training and Optimization:

The model's parameters are optimized to minimize the cross-entropy loss between the generated question Q and the target question Target_Question:

Loss = Cross_Entropy_Loss(Q, Target_Question)

6. Evaluation Metrics:

Quantitative evaluation metrics, such as BLEU, ROUGE, and METEOR, are computed to assess the quality of the generated question Q in comparison to the target question.

7. Validity Evaluation:

Human evaluators assess the coherence, correctness, and emotional resonance of the generated question Q_f. Qualitative feedback is collected to further analyze the quality of the generated questions.

5. Publically Available Existing Datasets

Dataset	Description	Application
SQuAD	Context passages with questions and answers for machine comprehension.	Question Answering
CoQA	Conversational dialogues with questions and answers, suitable for maintaining conversational flow.	Conversational Question Generation
MS MARCO	Documents with human-generated questions and answers, diverse for training and evaluation.	Question Answering
NarrativeQA	Books with summaries, questions, and answers, ideal for narrative context understanding.	Narrative Context Question Generation
CNN/Daily Mail	News articles and automatically generated summaries that can be treated as questions.	Summarization-based Question Generation
HotpotQA	Diverse and interconnected documents with questions, suitable for generating complex questions.	Complex and Interconnected Question Generation
DuReader	Chinese dataset with context, questions, and answers in narrative and dialog styles.	Chinese Language Question Generation
ARC	Science-related questions for testing reasoning abilities, involving logical reasoning.	Logical Reasoning Question Generation

Table 3. Publically Available Existing Datasets

6. Results

BLEU (Bilingual Evaluation Understudy): BLEU is a statistic that measures the degree of n-gram overlap between questions that were generated and questions that had been annotated by humans. A greater match between the produced and reference questions in terms of shared n-grams is indicated by higher BLEU scores. A BLEU score of 0.75, for instance, indicates that 75% of the n-grams in the produced question are the same as those in the reference question.

ROUGE (Recall-Oriented Understudy for Gisting Evaluation): ROUGE calculates the percentage of words in the produced and reference questions that are the same. To evaluate the effectiveness of matching word sequences, it takes accuracy, recall, and F1-score into account. A ROUGE score of 0.82 denotes a significant amount of word overlap between the produced and reference questions.

METEOR (Metric for Evaluation of Translation with Explicit ORdering): METEOR takes into account changes in word forms and word order while taking into account synonymy and word matching. It offers a more thorough assessment of question quality. The produced question has a decent degree of semantic alignment with the reference question, according to a METEOR score of 0.68.

Evaluation Metric	Description	Sample Value
BLEU	Measures n-gram overlap between generated and reference questions. Higher values indicate better match.	0.75
ROUGE	Measures overlap of word sequences between generated and reference questions. Higher values indicate better match.	0.82
METEOR	Considers word matching and synonymy, taking into account stemmed words. Higher values indicate better match.	0.68

Table 4. Evaluation Metric

Coherence: The degree to which the produced question fits the context of the supplied text is measured by coherence. The produced question is contextually relevant and makes sense within the provided information if the coherence score is high.

Correctness: The produced question must be grammatically accurate and syntactically correct to be considered correct. A question with a moderate correctness value is one that is grammatically sound but may have a few minor wording or structural problems.

Emotional resonance measures how well the produced question reflects the subtle emotional undertones found in the original material. When a system's emotional resonance value is low, it's possible that the system didn't completely understand the emotional components of the material of the created inquiry.

Aspect	Description	Value
Coherence	How well the generated question aligns with the context of the input text.	High
Correctness	Whether the generated question is grammatically correct and forms a coherent question.	Moderate
Emotional Resonance	The degree to which the generated question captures the emotional nuances of the input text.	Low

Table 5. Categorical Evaluation Metric

7. Conclusion

In conclusion, there is great potential for improving the quality and interest of created questions utilising the suggested autonomous subjective question creation system that uses a neural method with numerous filters. The system intends to produce WH-type questions from subjective content that are contextually relevant, emotionally resonant, and grammatically accurate by utilising cutting-edge neural architectures, attention processes, and the integration of numerous filters. It is clear from a thorough literature study that earlier methods had trouble coming up with subjective questions that were coherent, relevant, and emotionally balanced. To overcome these drawbacks, the suggested system's technique employs a sequence-to-sequence model with attention and includes grammar, context, and semantic filters. This method guarantees that the produced questions match the substance of the original material, have good grammatical construction, and reflect the emotional undertones expressed in the text. The case study provides more evidence of the system's potential benefits by showing how an online learning platform might use automated question development to encourage greater student involvement. Evaluation indicators like BLEU, ROUGE, METEOR, and human assessments are included to guarantee a full and comprehensive review of the system's performance. Even while the system has a lot of potential, it's vital to realise that there are still certain difficulties, notably in precisely capturing the many subtleties of subjective content and feelings. The model, attention processes, and filter implementations must all continue to be optimised by ongoing study. This research makes a significant contribution to more effective and efficient automatic subjective question generation, which has the potential to transform educational content, promote interesting conversations, and improve a variety of applications where producing high-quality subjective questions is crucial.

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