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Automatic Question Generation through Word Vector Synchronization using Lamma

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Abstract

According to previous research, the student's activities and participation are more significant than the visualization's content. One way to persuade students to communicate with a visual screen is to ask them to predict questions. This has been shown to assist students in learning. During algorithm exhibition, depending on the engagement category and the performance of question-response, we propose creating an autonomous question-generating system for interactive and deep learning. We demonstrate how to include more promising automatic question generation into the conventional design in this study, giving an entirely new approach to our system which is sentiment-based analysis. We also provide a set of hypothetical questions that may be generated mechanically founded on the data collected throughout the Generation. The findings and improvements in Automatic Generation accuracy with increased Blue and meteor scores are also shown in this paper.

Keywords: Seq2Seq; GPT; Question Generation.

Introduction

In Intelligent Tutoring Systems (ITSs), to achieve a certain goal, such as assessment and increased student engagement, several systems rely on asking questions. [1]. Furthermore, ITSs mimic the student's knowledge based on his or her responses to questions supplied. ITSs can customize their reinforcement and fundamental interaction with each student settled on the student model [2]. Since scientists have been blown away by neural network-based applications in several disciplines of natural language creation (e.g., machine translation, text summarization, and picture captioning), neural generation of questions is gaining traction in academia and business. Sequence -to-Sequence (Seq2Seq) learning, which builds an end-to-end QG model, was one of the first studies that did not rely on hand-crafted rules and advanced templates.

The goal of the generation system of questions is to hypothesize student understanding and concepts. The student framework, which is initialized by domain knowledge, is used in the question-generating process. Domain knowledge is a collection of hypotheses chosen based on their overlapping evidence to enable the creation of questions with indeterminate answers

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(There is more than one plausible hypothesis in the solution). When a student responds to a produced question, the framework is changed to reflect his or her response. [3] depict the updating procedure. When the updated student model is used to generate follow-up questions, the student misunderstandings that appear in the revised student model are recorded. Furthermore, the question production method adapts scholar understandings by creating queries with varying levels of complexity and range of evidence.

Motivation

We are inspired by the user's simple contact with Google, as well as Google's prompt responses. Another great source of inspiration is the recommendations presented for the query input by the user, as well as the possible questions and suggestions related to the query made by the user. One of the benefits of this sort of communication is that we can use the advice to add our knowledge of possible background inquiries and the types of questions that can be raised for any specific query or topic. This scenario is illustrated by the following simple example: when we enter or search the keywords what is research, Google automatically returns possible recommendations such as what is a research methodology, what is research design, what is a research paper, and many others, with the possibility of learning about or gaining new insights from this what is research query.

What is research?

- what is research
- what is research methodology
- What is research design
- What is research paper
- What is research design mcq
- what is research methodology pdf

Figure 1: Various Recommendations for the entered Query from Google Search Engine

Background

Questions of the type Multiple Choice Questions (MCQ), Boolean sorts of Questions (Yes or No), General Frequently Posed Questions (FAQ), paraphrasing Questions, and Question-Answer type can be asked to improve execution in the Teaching-Learning process. We will concentrate on the General FAQs. However, one well-known issue with topic models is that the degree of the generated questions frequently varies. Because automatic evaluation matrices do not provide promising results, this encourages and necessitates the evolution of several model evaluation procedures, most notably those based on the calculation of evaluation with the user feedback method. So, in addition to the evaluation metric score, it is a good practice to evaluate actual user input on the questions created in terms of naturalness and semantics to ensure that the performance is up to the mark.

Application

Question generation (QG) is a strategy for generating natural inquiries from a sentence or section of text. Question generation is used in education to lead to increased levels of reading comprehension resources. [4]. Question generation systems can also be used as Chatbot

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components (for example, to initiate a conversation or solicit feedback [5,44]. Alternatively, it could be used as a clinical instrument for assessing or improving mental health. In addition to the above-mentioned uses, question-generating systems can aid in the compilation of structured data sets for processing natural language (NLP) research in reading comprehension and question answers.

Advantages

Researchers and businesses are interested in question answering (QA) over knowledge bases (KB). The problems that test developers face in creating a large number of high-quality questions prompted the development of a generation of automatic question tools. AQG is focused on modifying algorithms for generating questions from organized (for example, databases) or unorganized information sources (for example, text). By reducing the cost (both in terms of finances and labor) of question formulation, AQG allows educators to devote more time to other important educational activities. A large majority of quality questions enable additional activities such as customized assessment [6], which aims to tailor learning to student knowledge and requirements and drill and practice exercises to be added to the teaching process [6].

Finally, the capacity to regulate question qualities like question difficulty and proficiency level automatically can aid in the creation of high-quality tests that match specified criteria.

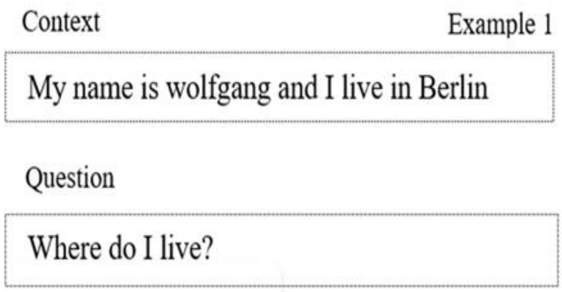

Figure 2: Sample Example of Question from input context

From the Simple above Example, when the context is the same as shown above, with the question Where do I live? one more question can be generated from the environment what is my name? So, with automatic Generation, we can explore the given Context completely, which makes the Teaching-Learning process very progressive.

Related Work

Question generation has evolved from a typical domain-based template-oriented system to an automatic Question generation system with powerful transformation models. While not as well-known as its twin activity Question Answering (QA), Question Generation (QG) [7] is nonetheless important task in NLP. Within an Artificial Intelligence (AI) model, the capacity to ask relevant questions demonstrates understanding [8]. As a result, the mission of QG is critical in the larger context of AI. In recent years, many investigations have resulted in solid

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models that perform well in QG. The most widely used technologies are Deep Learning-based strategies involving Sequence to Sequence [10, 45] models. These systems employ two Long short- term memory-based [11] neural networks, one for encoding the source context paragraph. The other network is for decoding the contained information and constructing a produced question [9]. More research that advances on traditional Seq2Seq-based QG models use either novel methods or features or sometimes both. Extra-linguistic capabilities [13] or the advent of solution-cognizance [14-16], [46] which makes use of the meant question's solution or the position of the answer within the context paragraph as additional capabilities. A mixture of those procedures has served as the foundation for the latest QG in recent years.

Other ways for performing QG have lately been proposed. Using policy gradients, Reinforcement Learning (RL) has provided accordant outcomes for the job [10]. Transformers [11] have also been employed in place of ordinary RNNs, due to the fact they offer the electricity of Attention to refer to specific factors of the context in the context paragraph Decreasing the RNN's reminiscence bottleneck [19] proposed a way for detecting duplicates in programming network question-answering websites. With about 404301 question pairs, they used three forms of functions: the importance of the question pairs, presence of associations, and vector space distance in the terms shaped among query pairs. They attained a reasonable accuracy of approximately 25%, which is higher than traditional methods. As a result, the questions have been categorized as redundant and relevant, with a most F-measure cost of 0.694. For computing the similarity between query pairings, other writers used dimensions that include the name of the question, its description, tag, and the topic to which it belongs. They tested stack overflow facts and discovered a remember price that became 10.2 instances better than in advance investigations [20, 47]. Deep gaining knowledge of approaches without problems recognizing rephrased sentences, according to a record by way of [21]. A labeled record is required for deep mastering techniques. However, we do not have enough labeled information to tell whether or not the question pairs are associated. Detecting comparable queries within the absence of a big amount of classified records is difficult. [12] recognized the traits of a terrible question. Too huge, meaningless, regularly occurring comments, deceptive phrases, socially beside-the-point content material, too many sentences, mistakes, garbled words, loss of statistics, and written in a foreign language, to name some. We recognize that clarity is a critical feature of a query, and to be able to obtain it, we make certain that the query generated has as tons relevant information as possible. Apply a textual content precis to a set of queries to assemble one of these questions. To seize the fundamental concept of any report, automatic textual content summarizing method was implemented. It is viable for the summary to be abstract or extractive. The extractive summary ranks the sentences and excludes the most vital ones, while the abstract method rewrites the unique fabric. The Extraction Summary method is usually recommended for generating FAQs from the FAQ group. Word embeddings [23] and BERT summarization [24] are two examples of deep mastering-primarily based summarizing that have recently gained recognition. In this observation, we additionally took into consideration the BERT-based Model.

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The majority of DG (Distractor Generation) methods now in use are based totally on various similarity measurements. WordNet-based metrics, Embedding-based similarities [25, 48], N-gram co-occurrence likelihood [26], phonetic and morphological similarities, structural similarities in an ontology, context similarity, context-sensitive inference, and syntactic similarity, as well as word difficulty level (Frequency) and parts of speech tags, are among them. In current years, VQA has been a popular research subject matter that mixes computer vision with natural language processing. Joint embedding, interest mechanisms, and compositional design are the three basic classes of VQA techniques. The RNN (Recurrent Neural Network) and CNN (Convolutional Neural Network) techniques are used to represent the question and image independently within the joint embedding technique, and then characteristic fusing is completed on the coarse degree to are expecting the answer [13], [27-29] [30, 49] proposed a complex template- based method that consists of semantic tagging statistics. [31] mentioned the usage of manually written policies over generated questions. [32] provided a deep Seq2seq version for producing questions for phrases taken from reading comprehension Datasets. In both automatic and human critiques, the technique performed higher than rule-primarily based techniques. The encoder-decoder fashions are used in interest-primarily based approaches, which might be customized implementations. For the problem of neural machine translation, the concept of attention was presented by [33]. In this situation, the supply and goal had been herbal language texts in two wonderful languages. Both texts had been aligned, and the source text words chargeable for producing every translated word have been discovered. [34] first attacked the QG utilizing an end-to-end attention-based encoder-decoder system. Their version, then again, ignores the intention solution, ensuing in questions with a high stage of randomness. [35,50] advised a context-aware sequential recommendation version based totally on interest that uses a gated Recurrent unit to dynamically manage the importance of various occasions for each object. While all of those methods are reliable, all of them rely upon superior fashions, additional capabilities, and tactics, making them extra tough to educate and replica. We display a way to use transformer-based fine-tuning processes to create robust query generation systems with just a single pre-skilled language version and no extra tactics, answer information, or functions in these paintings.

Proposed Methodology

The hassle announcement in the question era is that the part of the query is copied from the given text input in which the evaluation will be done on seq2seq generation which might be causes OOV (Out of vocabulary issue) and even without any data emotion detection the question is generated. This makes the repetition of the same meaning of questions as well reducing the accuracy. And as a result, in this, there are various wh questions generated without considering the subject and object of inputted data.

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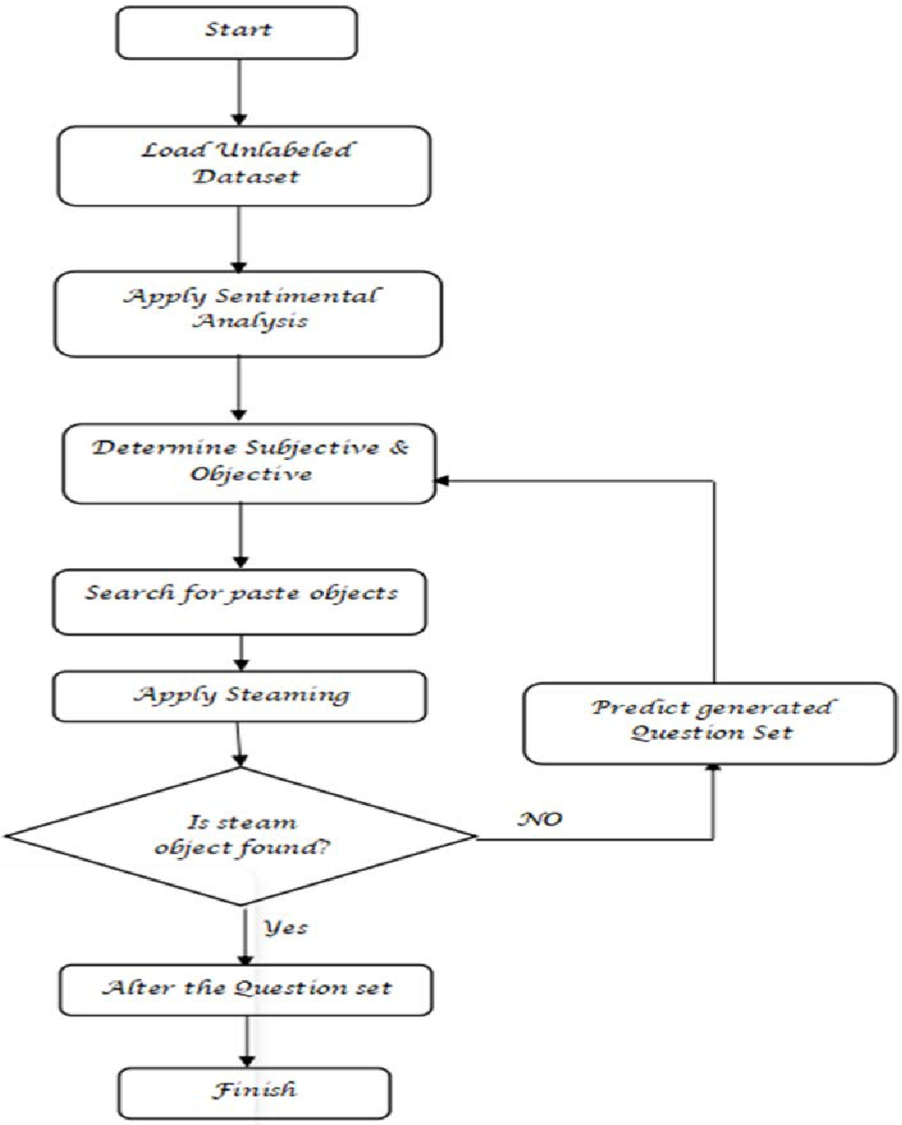

Figure 3: Pipeline of Proposed Automatic Question Generation Process

By looking toward, the problem from the existing conventional Automatic Question Generation Systems, the proposed methodology is going to be evaluated based on an evaluation of sentimental based analysis on inputted text in which the inputted data analyze and evaluate with the steaming-based evaluation in which the copy from question part will get evaluated & updated. The sentimental-based evaluation will give a new approach to the execution.

Load Unlabeled Dataset

The SQuAD (Stanford Question Answering Dataset) Dataset contains 100,000 questions, with over 50,000 of them being unanswerable. It also assesses a system's capacity to not only answer reading comprehension questions but also to avoid responding to questions that cannot be answered based on the provided text. For system training, SQuAD version 2.0 is employed.

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Apply sentimental Analysis

The language that was entered is processed through Pre -processing stages, and once the data has been cleaned, the Subject, Verb, and Object parts of the Query are analyzed, and subjective vs objective differences are discovered. Later, using the seq2seq model and Named Entity Identification and Parts of Speech tagging, the WH-preference type for the aim that was evaluated in previous phases is determined.

Search of Paste Objects

We look for the appropriate Object type in this phase of Paste Object Search when there are many object types in the same Query. The most appropriate object for the first and last preference is found first in these types of queries.

Stemming

We found the closest and related keyword to the target keyword in this step, which will later help us frame the most similar type of Questions. If we find a Paste object, we will change our current set; if we don't find a Paste object, we will find Wh preference, and then the Questions will be generated with the same objective found in previous stages.

In practically all Natural Language Processing (NLP) projects, stemming is one of the most used data pre-processing processes. Simply explained, stemming is the removal of a portion of a word or the reduction of a term to its stem or root. It's possible that we're not reducing a word to its dictionary root. To decide how to cut a word off, we apply a few algorithms. Complications stemming will occur from time to time. These issues are known as over stemming, which is the process of chopping off a significantly greater portion of a word than is required, and under stemming, which is the process of incorrectly reducing two or more words to more than one root word.

The overview of our system for subjective type Question generation is shown in the Figure below, where the main focus is Stage I, where we initially in the process of filtering, incorporated the Phase as sentiments assessment and attention so that later Phases don't have the problem of lack of meaningful information or the loss of some part of relevant information, and in later stages for justification of diversity among the Questions generated, We hired the second one-technology Generative Pre-educated Transformer, a gadget mastering version based on neural networks.

To generate textual content type, that is trained with internet facts. We used this sentimental evaluation to train with the Standard Stanford Question Answering Dataset, which helped us enhance results as indicated in the following section as compared to present conventional Question Generation Systems. If the input contains any extra information that isn't beneficial for later stages and so for Question generation then such extra information is dealt with by step 2 of the relevant Statement production process. As a result of this process, more significant keywords are extracted from the entire text content, and meaningful questions are formed from the input.

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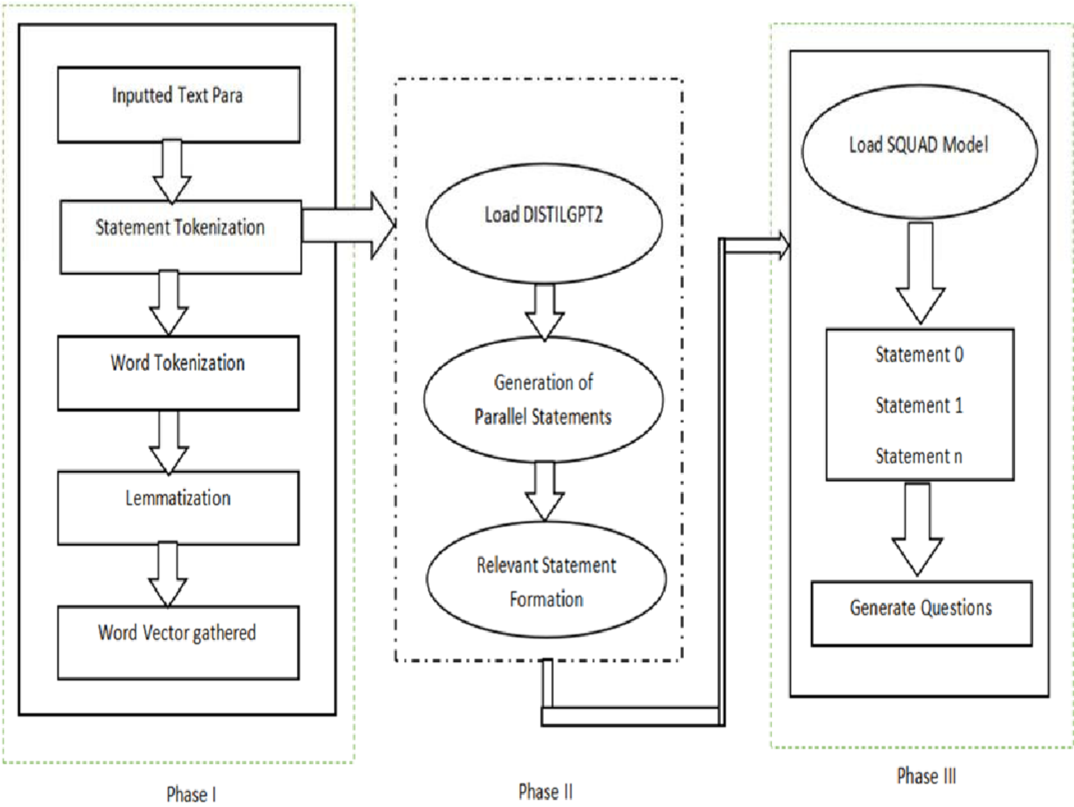

Figure 4: The overview of our system for Subjective type Question Generation Approach

Complete System From loading Input up to output Automatic Question Generation i.e from Phase I to Phase III through Phase II comprises of two main steps, one is to Pre-process given Input which later undergoes very important steps like to perform statement Tokenization on document input, then to find Word tokens, which are further useful to perform Lemmatization and to calculate word vector for every filtered word token extracted and this result is pass to Phase II where DISTILGPT2 Model is loaded and Parallel Statements are mapped into relevant Statements compared input document. Then these relevant statements are passed to Phase III When the SQUAD Model is used to teach the version and compared to which the many of the Automatic Questions are formed through 0,1,2……. N Numbers of Statements from Input.

Implementation

This section contains all of the fine details of the data preparation, parameters, suggested algorithm, objective evaluation, comparison studies, and outcomes, as well as the evaluation scores indicating improvement in the results.

Data Preparation

The Stanford Question Answering Dataset (SQuAD) version 1.1 became used to educate our question creation algorithm [36]. The data set will be loaded as a model, and API calls will be made to perform rapid and reliable execution. SQUAD is made up of paragraphs with questions and answers that are relevant to the paragraphs. The SQuAD comprises over

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100,000 questions and is used to generate QG on different platforms. It's a comprehensive collection of Wikipedia questions and answers. In the suggested QG, inputted paragraphs will be reformatted in various ways so that the meaning full question can be generated. Tokenization and word synchronization will be applied to the inputted paragraph, followed by the Lemmatization approach, which will result in new data generation.

The SQuAD is formatted to appear like language modeling input records. The Dataset as a whole has become a single text stream. For each education sample, a context paragraph and its relevant query(s) are combined into a single continuous sequence with a delimiter in among. A form of tactics may be used to convert the Dataset's authentic illustration (JSON) to a non-stop language modeling-equipped text.

Experimental Setup

Several ways can be used to execute the loading of the squad Dataset and the generation of the question. We employed the multi-meaning para construction in the proposal, which increases the difficulty of the question. Various strategies appear to operate on the Dataset in which different delimiters are used to separate the squad paragraph and pertinent question, but it appears to be confined to the development of a single question. Many models for question generating have been presented, but none have been found to focus on multi-meaning question generation. As a result, the DistilGPT2 [13] Transformer is recommended for the creation of necessary information, with the created statements being sent to various QG models as indicated below. The question is posed by this model. DistilGPT2 (short for Distilled-GPT2) is an English-language model that was pre-trained under the supervision of Generative Pre-trained Transformer 2's smallest version (GPT-2). DistilGPT2 can generate text in the same way that GPT-2 can. DistilGPT2 is an English-language model that has been pre-trained using GPT-2's 124 million parameter version. Knowledge distillation was used to create DistilGPT2, which had 82 million parameters and was supposed to be a faster, lighter version of GPT-2. The Open Web Text Corpus, an open-source replica of OpenAI's Web Text Dataset that was used to train GPT-2 [14], was used to train this transformer DistilGPT2. The texts were tokenized with the same tokenizer as GPT-2, a Byte Pair Encoding variation on the byte level (BPE). Knowledge distillation is a compression strategy that teaches a tiny student model to emulate the behavior of a bigger teacher model or a set of models.

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```
Input=Inputted_Statements
len_input =get_len(input)
If len_input <=1 then :
   Word=Word_Symetry()
   SyncWord=Word.Information()
   Sync_Para= SyncWord
else:
   state_token=StatementTokenisation(Input)
   Sync_Para=""
   for statement in state_token:
Sync_Statement=""
   word_token=Word_Tokenisation(statement)
   for singular_word in word_token:
    Sync_Word=""
if singular_word.isStopWord():
   Sync_Word= singular_word
Else:
     Try:
      Sync_Word_Vector=Word_Lammatisation(singular_word)
      Sync_Word= Sync_Word_Vector
      Except:
      Sync_Word= singular_word
Sync_Statement= Sync_Statement+ Sync_Word
Sync_Para= Sync_Para+ Sync_Statement
QG= InitializeQuestionGenrationModel()
List_Question=QG.getQuestions()
```

Figure 5: Proposed Algorithm Question Generation using word vector synchronization using Lamma (QGVWSL)

How to benchmark the automatic question generation

The most popular fact set in the field of herbal language processing is the Sandford question answering Dataset, and the maximum popular assessment indicators are the meteor, which is used to decide whether an ML version's candidate text resembles the reference text that is supposed to be generated and the Bilingual Evaluation Understudy or BLEU, which is a score that is used to evaluate a candidate's text translation toward one or extra reference translations. We utilize blue and meteor to determine the n-gram similarity between the reference sentence and the generated sentence primarily based on the questions in the SQuAD Dataset.

Model Setup

The proposed transform pretext is evaluated with a variety of hugging face models in this study. To track the effective question creation method, the supplied text is passed via multiple models. The proposed statement will concentrate on the creation of effective, relevant, and multimodal questions. The created question's reliability is assessed using metric and manual evaluations, with the efficiency being determined. Different Hugging Face Models are employed in this. T5- base-question-generator, t5 -small-squad2-question -generation, Bart-eqg-question-generator, and gpt2 question generation given paragraph are some of the models available.

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Baselines

Model 1 - T5-base-question-generator Hugging Face, this model is a sequence-to-sequence question generator, which accepts an answer and context as input and outputs a question. It is based on a t5-base model that has been verified. As an input sequence, the model takes concatenated replies and context and generates a whole question sentence as an output sequence. The maximum length of a sequence is 512 tokens. The following format should be used to organize inputs: < response> here is the answer text <context> here is the context text.

The model was fine-tuned on a Dataset that included SQuAD, CoQA, and MSMARCO, among other well-known Datasets. Concatenating the response and context fields into the previously specified format reshaped the Datasets. During training, the target was the question field from the Datasets. In the education setting, there had been around 200,000 examples. The version turned into training for 20 epochs at the schooling set, the use of a studying charge of 1e-3.

Model 2 - The T5 version become proposed in Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer, and it changed into best-tuned the use of SQuAD for QG. Transfer getting to know is a sturdy approach in natural language processing that includes pre-training a model on a facts-rich activity earlier than fine-tuning it on a downstream venture (NLP). The fulfillment of transfer mastering has inspired a slew of techniques, strategies, and practices. It was trained with the Squad Dataset, with sample 87599 as the training sample, and 10570 as the valid data sample.

Model 3 - Bart-eqg query generator, this version is a series-to-series query generator that accepts most effective the context as enter and outputs a query. It is trained at the EQG-RACE corpus and is primarily based on a pre-educated Bart-base model. The context is used as an input sequence, and the model produces a query as an output sequence. The maximum length of a sequence is 1024 tokens. The following format should be used to organize inputs Context. The input sequence can then be encoded and supplied to the model's generate () method as the input ids argument.

Evaluation Metric

The overall performance of query generation is evaluated via the subsequent metrics which itself indicates the generation of relevant information concerning the input.

BLEU [15]: The BLEU or Bilingual Evaluation Understudy, is a rating used to evaluate a candidate's text translation to one or greater reference translations. A best in shape is given a score of 1.0, while an excellent mismatch is given a score of 0.0

Each token is a 1-gram or uni-gram, and every phrase pair is a bigram assessment, so the approach compares n-grams within the candidate translation to n-grams in the reference text. The assessment is performed no matter phrase order.

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ROUGE-L [16]**:** ROUGE-L calculates n-gram recall by counting how many of the reference's longest common subsequences occur in the predictions.

METEOR [17]**:** Where recall weights are extra than accuracy, METEOR determines the harmonic imply of uni-gram precision and recall.

$$Fm(1-p) = M \tag{1}$$

Where;

Precision and recall are used to calculate the F-score is Fm

P is a chunk penalty

M is meteor score

Precision and recall are used to determine the F-rating, with the chunk penalty which gives a penalty based on the number of chunks in the candidate that map to chunks in the target or the reference.

Proposed System

Below shown is the Question Generated with various models (by T5, T5 fine-tuned on Squad and Bart-EQG) for the same Input Paragraph. We have added the multi-meaning Questions generated by our system also.

Table 1: Questions Generated by Proposed Model & Other Models

Input Paragraph	**Model 1**	**Model 2**	**Model 3**	**Proposed QGVWSL**
Temples typically have a main building and a larger precinct, which may contain many other buildings, or maybe a dome-shaped structure, much like an igloo. The word comes from Ancient Rome, where a templum constituted a sacred precinct as defined by a priest, or augur.	What is a temple-shaped structure ?"?"?"?'?	What type of structure is a dome?	What kind Of building is a temple?	Q-01: What may a Temple have and a larger precinct? Q-02: Who may have a Main building and a larger precinct?

Objective Evaluation

This section reflects the automatic evaluation of the generated output. The evaluation was performed with BLUE and METEOR. Model 1 has scored 0.010066 blue-1 and 4.18 meteor score which is successively increasing from T5 fine-tuned model to Bart-eqg based generator

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and for our model its 0.191051, blue-1 and scored up to 25.00 meteor which is considerably better than the conventional generators.

Table 2: Evaluation Results of our system and other models

AQG Models	BLUE_1	BLUE_2	BLUE_3	BLUE_4	METEOR
Model 1	0.010066	-	-	4.18	10.26
Model 2	0.010261	-	-	8.89200	7.211
Model 3	0.023254	-	-	1.19	10.18
DISTIGPT2+QG	0.191051	0.140104	0.129726	14.189	25.00

Table 3: Comparative analysis of our system with many of existing cutting-edge techniques

Model	BLEU-4	METEOR
Du et al. (2017) [18]	12.28	16.62
Du and Cardie (2018) [19]	15.16	19.12
Zhao et al. (2018) (s2s+a) [20]	4.8	12.52
Zhao et al. (2018) (s2s-a-at-mcp-gsa) [20]	**16.38**	20.25
Luis Enrico Lopez et al (2020) [21]	8.26	21.2
T5 Model	4.18	10.26
T5 base fine-tuned on the squad	8.89200	10.18
Bart-eqg-question-generator	1.19	10.18
Distilgpt2+QG (Ours)	**14.189**	**25.00**

Our model Distilgpt2+QG is as compared with many of the modern-day Question Generators and results have shown that our system achieves a great meteor score with a good increase in blue score.

Conclusion & Future Scope

The suggested Subjective Generation pipeline has shown that automated Question generation can be used to generate Subjective type Questions in the education area. This is a robust system that works not only for document input but also for single sentences, which has been a long-standing issue in the Automatic Question Generation domain. We also demonstrated that the system can create many questions from a single input sentence with improved semantics and fewer grammatical problems. As stated above, this approach has produced amazing outcomes. We have supplied user feedback as a reward system to justify exceptional results, with greater blue and meteor scores for identifying the diversity of created output.

We have applied various filters to Questions created to maximize accuracy and hence raise the overall score promisingly, similar to how we used a multi-level filter to avoid losing sentiments from the input.

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