

cationa Jeneral Juestion 1

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Contributions

Datase

- **T**5 novel question generaa fine-tuned model for educational purposes. tion pipeline using B Designed
- Leveraged the SQuAD dataset for rocontext-question pair preparation and fine-tuning. bust
 - scripts text and PowerPoint slides into structured datasets. preprocessing to process raw • Implemented
- datasets performance optimized model through prompt engineering. Fine-tuned T5 and

alignment.

- Grouped the dataset by context as the unique key.

• Data Preparation and Grouping:

- signifi-BLEU similarity, achieving with models semantic cant improvements. grammar metrics, Evaluated ROUGE,
 - for usergenerating questions from user provided text or PowerPoint inputs. tools user-friendly Developed

Proces

Proposed Method

SQuAD:

Answer Input: Context, Question

lection of question-answer pairs. The questions in the dataset are based on a set of Wiltimas: such that it requires the model to crafted extract a span from the passage. set of Wikipedia <u>.</u>S Each question dataset SQuAD Context: ticles.

What is the SQuAD dataset? Question:

Answer:

a collection of question-answer pairs. SQuAD dataset is The

Proposed: Question Generation

Question 个 Context

widely Albert Einstein was a theoretical physicist who developed the theknown for his mass-energy equiv He is relativity. alence formula. Context: ory of

of rel-**Question:**Who developed the theory o ativity?

"Some on 1?" on 2?" Question Question Question Ω Ω Ω -H -H -H

• Step 2: Fine-Tuning the Model

- Train the T5 model with SQuAD dataset variants
- Implement prompt-based variations for diverse

• Step 3: Model Evaluation

- and semantic similarity generated questions - Evaluate the model using BLEU, ROUGE, in grammar consistency - Analyze
- Generate new questions based on user-provided context (text/PPT) Step 4: Question Generation
 - Provide diverse output with various prompt types

Examples

Tuned Model Sample Validation and Generated Question Fine

and such Quran, teachers, su outh pastors h as the Qura pastors/youth such spiritual texts and rabbis, religious "Religious mullahs teach Bible may as gurus, lamas, ma OK аh Tor

context

Ф

sample

Example Dataset Format

ext

"cont

-Suitable for training models in question generation and comprehension.

100,000 question-answer pairs across diverse articles.

- SQuAD: Stanford Question Answering Dataset.

Dataset Overview:

= =

questions":

religiou α for name al genera another "ground_truth_c "What is anoth teacher?", ₩What

Quran?",

the

-⊢ Ω

text

O F

type

igious ike rel \vdash WOrk α Ŋ Q Q used from teach Ф Р might 0 11y = general teach. that text teacher to "Who would Quran, Tora α "Name

the

igious rel some are ™What names? "generated_question": teacher spiritual and }

Prompt Variants Sample

- ants
- context context the the ON based On based short question base creative question prompt_varia "Generate a "Generate a "Generate a α
- context",
 context:",

- α
- the ON based
- context the On based ש ש

Results

- Format data to fit the fine-tuning requirements

- Group contexts and their related questions.

- Remove invalid or incomplete entries

- Prepare raw datasets for model input.

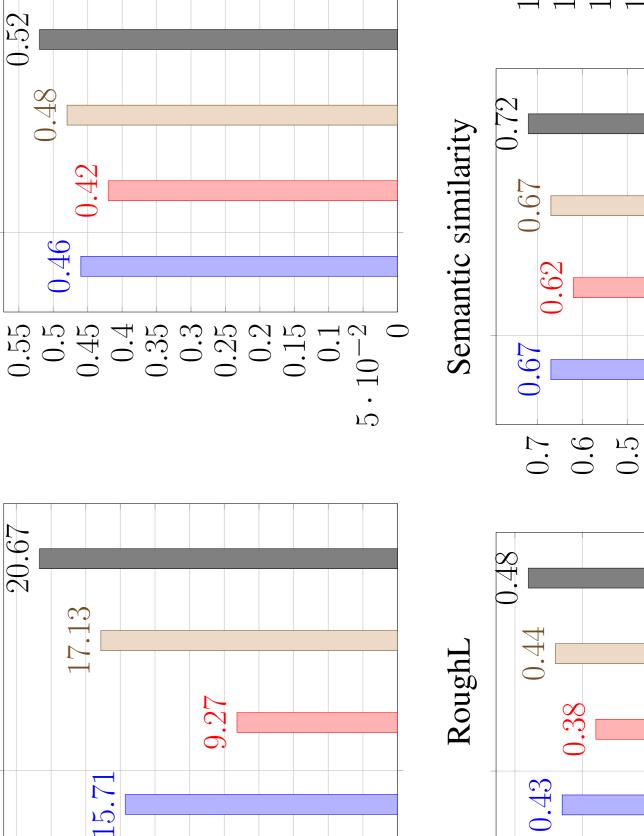
Step 1: Data Pre-Processing

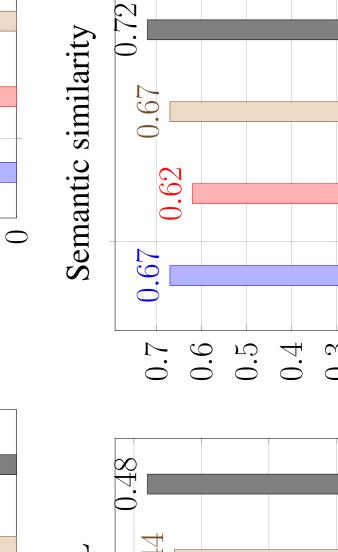
- Performance Comparison:
- Achieved a 32% increase in BLEU score, indicating better alignment with ground-- The fine-tuned model outperformed the base model across almost all metrics.

- ROUGE scores improved significantly: ROUGE-1 (+11%), ROUGE-2 (+26%), and ROUGE-L (+12%). truth questions. -ROUGE
 - Semantic similarity increased by 7%, demonstrating enhanced contextual relevance in the generated questions
- Grammar issues were reduced by 9%, though there is still room for further improve ment.

• Performance Visualization:

- Compared models: Base model, IT5 model, T5-small-SQuAD2-question-generation, and the fine-tuned model.
 Metrics analyzed: BLEU, ROUGE (1/2/L), Semantic similarity, and Grammar quality.





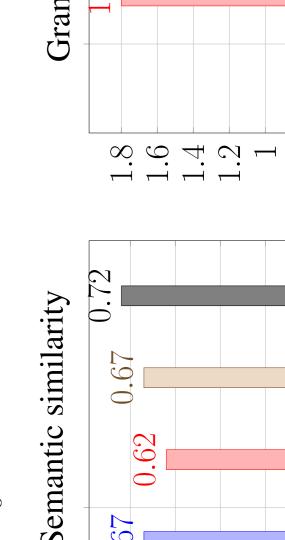
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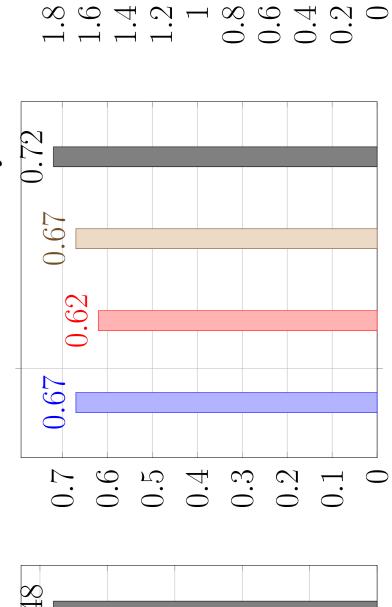
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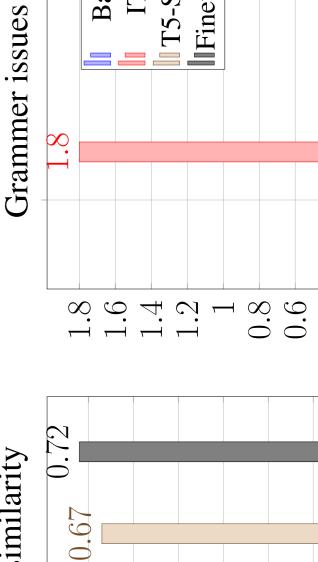
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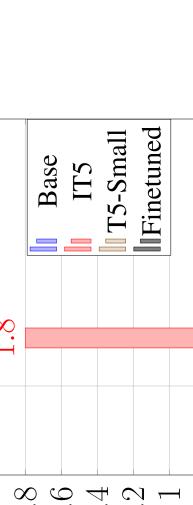
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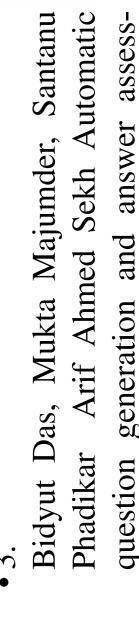


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0.16

0.14

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Pre-trained

with

Generation

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guage Models

Sahan Bulathwela, Hamze Muse and Emine Yilmaz Scalable Educational Ques-

and Fernando Alva-Jose Camacho-Collados

for

Models

Language

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References

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0.3

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20.67

Bleu

Rouge1

0.17

0.2

0.15

0.1

10

Rouge2

Paragraph-Level Question Generation

