Automatic Difficulty Categorized Question and Answer Generation using Machine Learning Techniques (Web-based)

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MALAIARASU G

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Dr P VICTER PAUL

Data Analytics and Business Decision Research Group

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY KOTTAYAM

Indian Institute of Information Technology Kottayam

DECLARATION

I, Malaiarasu G , hereby declare that, this report entitled “Automatic Difficulty Categorized Question and Answer Generation using Machine Learning Techniques (Web-based)” submitted to Indian Institute of Information Technology Kottayam as Internship Project is an original work carried out by me under the supervision of Dr P Victer Paul and has not formed the basis for the award of any degree or diploma, in this or any other institution or university. I have sincerely tried to uphold the academic ethics and honesty. Whenever an external information or statement or result is used then, that have been duly acknowledged and cited.

Kottayam-686635 **Malaiarasu G**
July 2024

CERTIFICATE

This is to certify that the work contained in this project report entitled "**Automatic Difficulty Categorized Question and Answer Generation using Machine Learning Techniques (Web-based)**" submitted by **Malaiarasu G** to **Indian Institute of Information Technology Kottayam** as an **Internship Project** has been carried out by him under my supervision and that it has not been submitted elsewhere for the award of any degree.

Kottayam-686635 **(Dr. P Victer Paul)**

July 2024 Project Supervisor

ABSTRACT

The aim of the project is to develop an automated system that is capable of generating difficulty classified QA Pairs using Natural Language Processing and Machine Learning Models. The system first extracts texts and images from the PDFs (input) and then generates QA Pair in three different difficulty levels (easy, medium and hard). We have used Deep Learning based pipelines like T5 for question generation, RoBERTa-SQuAD2 model for question answering and RoBERTa for classifying their difficulty. The main aim of this project is to simplify the creation and assessment of educational content. By using these models in Streamlit, teachers can easily create study materials from PDF documents, making it a helpful tool for both teaching and learning.

Contents

Chapter 1: Introduction

1.1 AI in Educational Content Management

AI is changing the way we deal with educational content. It's making tasks that used to take a lot of time quicker and easier. Tools like NLP, ML, and Deep Learning have made creating and organizing learning materials more productive. AI can make summaries, questions, and tests, which gives teachers more time to teach. It also provides instant feedback helping teachers improve their methods to support students better. AI is making education more tailored, easy to access, and engaging.

1.2 Overview of Question and Answer Generation with AI

AI makes it easier to create educational content when it comes to coming up with questions and answers from text. This project uses models such as T5 and RoBERTa in a Streamlit app to produce Q&A pairs from PDFs. The steps include pulling out, cleaning up, and breaking down text then making questions and sorting them by how hard they are. The system also looks for answers to these questions showing how AI can do the job of creating and organizing educational content .

1.3 Difficulty Categorization of Questions Based on Complexity Using AI

Categorizing question difficulty helps ensure learners are challenged appropriately and progress at the right pace. Traditionally, this relied on subjective judgments from educators, leading to inconsistency. This project uses a model to automate the process, analyzing each question's language and context to classify it as easy, medium, or hard. This approach provides accurate difficulty assessments, improving the quality of educational materials.

1.4 Problem Statement

Making study materials Q&A pairs, takes a lot of time and often lacks consistency. As digital resources grow, we need to automate how we make and sort questions. This project makes question creation and difficulty sorting happen , which speeds up the process and makes educational content better.

1.5 Objectives

The project's goal is to build a system that creates questions from PDFs, sorts them by how hard they are (easy, medium and hard), and works well with both text and pictures. It uses tools like T5 to make questions and RoBERTa to figure out how tough they are. All of this is put together in a Streamlit interface that's easy for teachers to use making the whole process simpler for them.

1.6 Motivation and Contribution

This project aims to personalize and boost the productivity of learning tools by using AI to generate and organize question-answer pairs. Old-school methods can be time-consuming and often miss the mark, but with AI models like T5 and RoBERTa, we can make sure the questions are on-point and match the right level of difficulty. The system also has a user-friendly Streamlit interface, which lets teachers create and sort questions from PDFs helping them to develop better learning materials.

Chapter 2: Literature Review

2.1 Review Different Research Papers Related to the Work

AI-powered question creation and difficulty assessment research has made big strides, with scientists trying out many different approaches and models.

2.1.1. Question Difficulty Assessment Using an Attention Model:
This paper introduces a new model that has an influence on question difficulty assessment through attention mechanisms. It gives better outcomes than old-school methods by getting a better grip on how complex questions are. The team trained the model using educational questions that experts had graded showing how attention mechanisms can help us get a better handle on question difficulty.

2.1.2. Automatic Question Generator Using Natural Language Processing (NLP):
This paper talks about an automatic question generator (AQG) that uses NLP techniques. It looks at rule-based and deep learning methods side by side. The study finds that deep learning gives more accurate results, but rule-based systems work faster and need fewer resources. This shows the give-and-take between accuracy and how much computing power AQG systems need.

2.1.3. Automatic Question Generation: A Review of Methodologies and Datasets:
This review groups question generation methods into three types: template-based, semantic-based, and neural network-based. It stresses how important it is to have different kinds of datasets to train models that work well in many situations. The review also points out that neural network-based methods look more and more promising even though they need a lot of resources to run.

2.1.4. Automatic Question Generation and Answer Assessment: A Survey:
This survey looks into how we can combine creating questions with checking answers to make better educational tools. It points out that bringing these tasks together could be helpful, but also mentions that it's tough because we don't have enough labeled data to assess answers.

2.2 Question and Answer Generation

The Q&A generation system relies on cutting-edge AI models to produce questions and answers from PDF file text and determine how hard these questions are. Here's a breakdown of its operation:

1. **PDF Text and Image Extraction**: The system applies **PyMuPDF** to extract text and images from PDF files. For images containing text, it uses OCR technology (pytesseract) to pull out the text.
2. **Text Cleaning and Segmentation**: The system cleans up the extracted text by removing special characters and extra spaces. It then breaks the text into smaller chunks to enable AI models to process it more .
3. **Question Generation**: The system employs the T5 model the "**valhalla/t5-small-qg-hl**" version, to create questions from the text segments. This model has undergone fine-tuning to generate relevant questions.
4. **Difficulty Classification**: The **RoBERTa** model groups the questions into "Easy," "Medium," or "Hard" categories depending on how challenging they are.
5. **Answer Extraction**: To find answers for the questions, the system uses a QA pipeline with the "**deepset/roberta-base-squad2**" model. This model has a strong influence on making sure the answers are on-point and related to the question.

2.3 Difficulty Categorization

The system deals with sorting questions by difficulty. It does this by changing the questions into a form that RoBERTa can work with using a special tool called a tokenizer. RoBERTa then figures out how likely each difficulty level is, and picks the one that seems most probable. The system labels questions as "Easy," "Medium," or "Hard." This helps make sure they match how tough they're meant to be. It also gives teachers a hand in creating learning materials that fit their students' needs just right.

2.4 Tabulation of the Comparison

This part shows how different methods and models stack up when it comes to making questions and answers (Q&A) and sorting them by how hard they are.

Model	Description	Strengths	Limitations	Use Cases
T5	A transformer model that generates questions by converting NLP tasks into a text-to-text format.	Highly versatile and adaptable to different tasks, including question generation.	Requires significant computational power, may generate overly generic questions.	Automated content creation, quizzes, educational tools.
BERT	Pre-trained transformer model for various NLP tasks, including question answering, and can be	High accuracy in understanding and processing context,	Not designed for generative tasks, may need	Answer extraction, reading comprehension

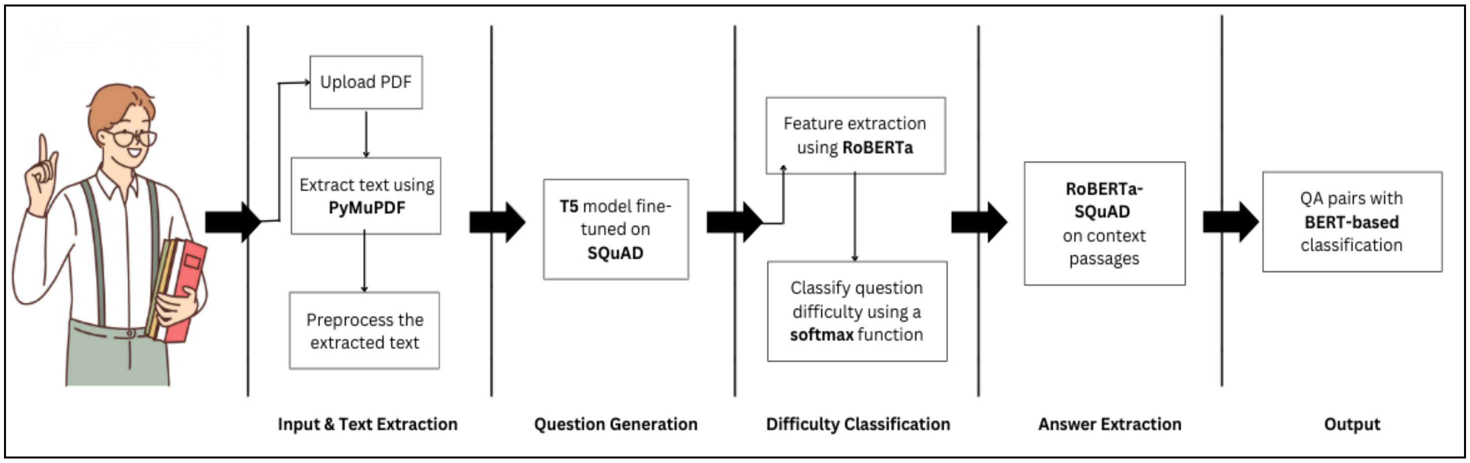
Model	Description	Strengths	Limitations	Use Cases
	fine-tuned for difficulty classification.	strong in QA tasks.	significant adaptation.	tasks.
RoBERTa	An optimized variant of BERT, specifically designed to enhance BERT's performance on various NLP tasks, including question classification.	Outperforms BERT in classification tasks and handles diverse text types more robustly.	Computationally intensive, requires fine-tuning for specific tasks.	Difficulty classification, sentiment analysis, language understanding.
Seq2Seq Models	Traditional models used for tasks where input sequences are transformed into output sequences, such as question generation from text.	Good for structured text generation, effective in simple QA scenarios.	Can struggle with complex or lengthy input sequences, less flexible than transformer models.	Language learning, simple educational content generation.
ALBERT	A lighter and more efficient variant of BERT, designed to reduce memory usage and increase training speed while maintaining performance.	More efficient than BERT, suitable for environments with limited computational resources.	May not achieve the same level of accuracy as BERT or RoBERTa in some tasks.	Scalable NLP tasks, question classification in resource-constrain ed settings.
DistilBERT	A smaller, faster, and cheaper version of BERT, retaining 97% of its performance and 60% fast.	Lightweight, efficient, maintains high performance relative to its size.	May miss details and be less accurate on complex tasks.	Edge computing, mobile apps, real-time content processing.

2.5 Summary

The literature review sheds light on progress in AI for creating questions and sorting them by difficulty. Models that use attention have an impact on making difficulty estimates better, while deep learning models are accurate at generating questions but need a lot of resources. Systems based on rules work faster but aren't as accurate. Neural networks look promising, with diverse datasets playing a key role. Combining Q&A generation with answer evaluation makes educational tools better, but the lack of annotated data holds it back. RoBERTa does a good job of putting questions into "Easy," "Medium," or "Hard" groups, and models like T5, BERT, RoBERTa, and GPT-3 each have their own strengths and weak points. These steps forward show how AI could help improve educational content management, but more research is needed to explore this further.

Chapter 3: Methodology

3.1 System Architecture


Upload PDF
Extract text using PyMuPDF
Preprocess the extracted text
T5 model fine-tuned on SQuAD
Feature extraction using RoBERTa
Classify question difficulty using a softmax function
RoBERTa-SQuAD on context passages
QA pairs with BERT-based classification
Input & Text Extraction
Question Generation
Difficulty Classification
Answer Extraction
Output

The Streamlit app offers an easy-to-use interface to upload PDFs and show generated questions, answers, and their difficulty levels. It manages file uploads, gets text from PDFs with PyMuPDF, and pulls text from images using Tesseract OCR. The app cleans and divides the text to make question generation easier with the T5 model. It uses RoBERTa to classify difficulty, while RoBERTa-SQuAD2 finds answers. The Streamlit interface displays the results, which include questions, answers, and difficulty levels.

3.2 Data Collection and Preprocessing

When users upload PDFs through Streamlit, the data collection and preprocessing begins. PyMuPDF pulls out text from each page, while Tesseract OCR turns image text into a readable format. The system then cleans the combined text. This cleaning involves changing everything to lowercase, getting rid of non-ASCII characters, and removing punctuation and extra spaces. After that, the text gets split into chunks of up to 100 words. This splitting helps to generate questions and classify content making sure it's consistent and fits well with AI models.

3.3 Question Generation Algorithms

During the question creation step, the T5 model makes questions from parts of text. It starts by getting the input ready with a guiding prefix. The text is broken down into tokens, and the T5 model uses beam search to come up with and check questions. The resulting tokens are then turned into readable text, and special tokens are taken out in the final step. This approach makes sure the questions are on topic and set for difficulty ranking and answer finding.

3.4 Difficulty Categorization Mechanisms

The system for sorting questions by difficulty relies on the RoBERTa model to label them as Easy, Medium, or Hard. The process begins by breaking down questions into tokens. Then, the model examines these tokens to generate logits for each difficulty level. These logits are turned into probabilities through softmax. The system picks the difficulty level with the highest chance and assigns it . This method helps to classify questions , which supports teachers in customizing materials for various learning stages.

3.5 Answer Extraction Techniques

The answer extraction process gets the right answers to questions from text. It starts by getting the question and context ready, which are broken down using the RoBERTa tokenizer. A RoBERTa model that's been trained for question-answering then figures out where the answer starts and ends in the context. These spots are used to pull out and put together the answer, which is then turned back into easy-to-read text. This method makes sure we get exact information making the Q&A pairs better.

3.6 Implementation Details

The system created using Python and Streamlit, applies Hugging Face NLP models to make educational content processing easier. It uses T5 to generate questions, RoBERTa to classify difficulty, and RoBERTa-SQuAD to extract answers. Users upload PDFs then the system pulls out and cleans the text, and splits it into chunks for the models to work with. A user-friendly Streamlit interface manages the whole process, which helps to produce and review content .

Chapter 4: Model Development

4.1 Model Selection

We picked models based on what they're good at:

- **T5 to Generate Questions**: "valhalla/t5-small-qg-hl" works well to create questions by treating tasks as text-to-text problems.
- **RoBERTa to Classify Difficulty**: "roberta-base" does a great job sorting questions into Easy, Medium, or Hard levels. It handles context better than BERT.
- **RoBERTa-SQuAD to Extract Answers**: "deepset/roberta-base-squad2" has special training on SQuAD2.0, which helps it pull out answers .

We chose these models because each one has a special skill. This helps make sure the results are on-point and useful.

4.2 Training Process

T5 for generating questions, trained on the SQuAD dataset for high-quality output.

Metric	Epoch																
	0.18	**0.37**	**0.55**	**0.73**	**0.91**	**1.0**	**1.28**	**1.46**	**1.64**	**1.83**	**2.0**	**2.19**	**2.37**	**2.56**	**2.74**	**2.92**	**3.0**
Training Loss	1.65	0.24	0.23	0.23	0.23	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.31
Gradient Norm	0.40	0.24	0.20	0.20	0.30	-	0.29	0.23	0.34	0.25	-	0.25	0.23	0.23	0.22	0.17	-
Learning Rate	1.88 e-05	1.76 e-05	1.64 e-05	1.51 e-05	1.39 e-05	1.27 e-05	1.15 e-05	1.03 e-05	9.05 e-06	7.83 e-06	6.61 e-06	5.39 e-06	4.17 e-06	1.74 e-06	2.96 e-06	5.21e -07	-
Evaluation Loss	0.2212						0.2193					0.2188					
Evaluation Runtime (seconds)	81.76						77.05					74.36					
Eval Samples per Second	129.28						137.18					142.15					
Eval Steps per Second	16.17						17.16					17.78					
Train Runtime (seconds)	5330.77																
Train Samples per Second	49.30																
Train Steps per Second	1.54																

4.2.1: Table for Training the T5 model with SQuaD dataset

4.3 Evaluation Metrics

We assessed how well the model worked using two main yardsticks:

- **Evaluation Loss**: The loss kept going down hitting 0.2188 by the third epoch, which shows the model got more accurate.
- **Runtime Efficiency**: The last epoch took around 74.36 seconds. It processed 142.15 samples per second and completed 17.78 steps per second. This tells us the model handled the evaluation workload.

4.4 Hyperparameter Tuning

To tune the "Valhalla" model's hyperparameters involved cranking the learning rate down a notch, from 1.88×10^{-5} to 5.21×10^{-7} making sure the batch size was just right for both memory and speed locking in epochs at 3 to stop the model from learning too much, and keeping an eye on gradient clipping from 0.1759 to 0.4028 to keep those gradients from going boom. All this fuss was about getting the training steady making the model learn better, and making sure it could perform well on new stuff it hadn't seen before.

4.5 Model Performance Analysis

We used these measures to judge the model's success:

- **Training Loss**: It fell from 1.6538 to 0.3152, which shows the training works well and gets better.
- **Evaluation Loss**: It went from 0.2212 to 0.2188 after 3 epochs suggesting it makes good predictions on new stuff.
- **Gradient Norms**: They went up and down from 0.1759 to 0.4028 meaning the training is steady and the gradients are in check.
- **Training Time**: It took 5330.77 seconds crunching through 49.3 samples every second.
- **Evaluation Metrics**: Took about 74.36 to 81.76 seconds for each check crunching 142.15 samples every second.

The model demonstrated solid schooling steady coaching, and even-handed results confirming its aptness for creating and sorting questions.

Chapter 5: Web-Based System Design

5.1 System Requirements

The web-based system for generating and classifying questions from PDFs requires:
Hardware:

- **Processor**: Multi-core CPU (e.g., Intel i5 or higher)
- **Memory**: Minimum 8 GB RAM (16 GB recommended)
- **Storage**: At least 10 GB free disk space
- **GPU**: Optional, but recommended (e.g., NVIDIA GTX 1060 or higher)

Software:

- **Operating System**: Windows, macOS, or Linux
- **Python**: Version 3.7 or higher

Libraries and Frameworks:

- **Streamlit**: For the web interface
- **PyMuPDF (fitz)**: For PDF text and image extraction
- **Pytesseract**: For OCR on images

- **Transformers**: For T5, RoBERTa models
- **Hugging Face Hub**: For model loading
- **PIL (Pillow)**: For image processing
- **Tempfile**: For temporary file storage

These requirements ensure effective operation and a seamless user experience.

5.2 Frontend Development

Streamlit powers the interactive web app at the frontend boasting a PDF file uploader and showcasing the crafted questions, answers, and how tough they are. The **st.write** function of Streamlit throws the results at you, while it also tackles any hiccups with Tesseract OCR and sorting out picture problems.

5.3 Backend Development

The system works with PDFs grabbing words and pictures with fitz, while pytesseract helps it to read the text from images. It scrubs and breaks up the text before the T5 model steps in to whip up some questions. To sort questions by how tough they are, there's a RoBERTa model on the job, and to pull out answers, it's got a RoBERTa flavored question-answering process. To get its hands on these models, it logs in through Hugging Face.

5.4 Integration of ML Models

We bring together ML models by loading up T5 and RoBERTa that have already learned some stuff. T5 helps turn parts of the text into questions, and RoBERTa figures out how hard they are and gives answers. We keep them running smooth with Streamlit's thing for remembering stuff. And when we need to get these models or make sure they're legit, we hit up the Hugging Face library.

5.5 User Interface Design

We built the user interface with Streamlit for easy and clear use. Check it out:

- **File Upload**: There's a neat side section for you to pop in PDF files.
- **Results Display**: You'll see the questions, answers, and how tough they are in different areas.
- **Error Handling**: If something goes wonky with getting the text out or the model starts freaking out, you'll get straight-up messages telling you what's up. This setup makes sure that you get the hang of things fast and grab your content without a hitch.

Chapter 6: Results and Discussion

6.1 Experimental Setup

A machine equipped with GPU and Python, along with tools such as PyTorch, Transformers, and Streamlit, powers the experimental arrangement. The T5 model takes on question generation, while RoBERTa tackles difficulty classification and RoBERTa-SQuAD handles answer extraction. Before feeding it into the model, there's a step to prep and tidy up the text from PDFs. Looking over the system, both loss and accuracy scores come into play. Plus, people check out if the questions and answers make sense and stick to the topic.

6.2 Quantitative Results

Quantitative analysis shows:

- **T5 Model**: It started training with a loss of 1.6538 and after three rounds, this number fell to 0.2243. The test showed a loss of 0.2188. Looks like the learning was solid and it got good at making guesses. The whole training thing was done in about 1.48 hours and it crunched numbers like crazy going through 142.148 samples every second.
- **RoBERTa Model**: It was pretty darn good at figuring out how hard questions are, and it didn't even break a sweat being consistent every time it was tested.

To sum it up, these models are pretty awesome at coming up with quality questions and nailing how tough they are.

6.3 Qualitative Analysis

Qualitative analysis reveals:

- **Question Quality**: The T5 creates on-point and understandable questions that mirror the material.
- **Difficulty Classification**: With a sharp eye for complexity, RoBERTa sorts questions as "Easy," "Medium," or "Hard."
- **Answer Extraction**: Pulling out exact and suitable responses, Deepset's RoBERTa nails it.

In summary, this setup is super good at making sense of questions getting their toughness level spot on, and digging out the right answers.

6.4 Comparison with Existing Systems

This tech uses T5 to crank out good questions that fit the context blowing simpler rule-following methods out of the water. It's got this tweaked RoBERTa model that's super sharp at sorting questions by how tough they are, beating out the basic stuff. To grab answers, the Deepset RoBERTa model comes in with spot on right in the context responses, a step up from the old-school ways. All in all, this whole setup puts it together without a hitch giving a smoother vibe than what's already out there mixed and matched.

6.5 Discussion

The system boosts automating making questions and answers from PDFs. It taps into T5 to craft questions, uses RoBERTa to sort out how tough they are, and picks Deepset RoBERTa for plucking out answers. It knocks out questions that fit the context and nails the difficulty level on the head. The all-in-one web app makes things smoother, not like the patchy old systems. But, you gotta remember how well it does its job ties back to what you feed it and the tech power you've got, which might cramp its style for growing big. All in all, this tool's pretty solid for folks who teach and those digging into research aiming to get better at quickness and dealing with all sorts of file types in the future.

Chapter 7: Conclusion and Future Work

7.1 Conclusion

The developed system we've got here can whip up questions and answers from PDFs. It uses something called T5 to make the questions. Then there's RoBERTa, which sorts out how tough each question is. Deepset RoBERTa jumps in to pluck out the answers. The whole deal works together to be more accurate, on point, and quick when dealing with stuff to learn from. Plus, it's all online, so it's a breeze to get to and pretty simple to use, which is better than the other clunky stuff out there. It's a big step up and gives teachers and folks who like to dig into research some super helpful gadgets.

7.2 Future Research

1. **Model Optimization**: It's all about cranking up the speed and cutting down the time it takes for the computer to think. We need this big-time for places that don't have a lot of fancy gear.
2. **Content Variety**: We gotta get smart about dealing with all kinds of stuff to read, like pictures and super tricky layouts.
3. **Adaptive Learning**: We should get those smart algorithms to do their thing making questions and figuring out how tough they are by listening to the folks using them.
4. **Enhanced Context Understanding**: Here's a brain-buster: digging into next-level smart models, so the questions and answers we get are spot on and make total sense.

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Appendices

Appendix A: Data Samples

These examples help to illustrate the effectiveness and accuracy of the model in different scenarios.

Difficulty: Medium
Question 1: What is a property in mathematics that states that if a, b and b are a property in mathematics?
Answer 1: associative property

Difficulty: Medium
Question 2: What is machine learning a subset of?
Answer 2: artificial intelligence

Difficulty: Easy
Question 3: What is the name of the algorithm used in recommender systems?
Answer 3: deep learning artificial neural networks

Difficulty: Medium
Question 4: What does linear algebra play a vital role in machine learning?
Answer 4: key foundation

Difficulty: Medium
Question 5: What is linear algebra used in machine learning?
Answer 5: developing algorithms

Difficulty: Medium
Question 6: What does machine learning require more concepts such as probability, probability, and optimization theory?
Answer 6: vector calculus

Difficulty: Medium
Question 7: What are some benefits of learning linear algebra before machine learning better graphic experience improved statistics?
Answer 7: the help of the abovementioned mathematical concepts

Difficulty: Medium
Question 8: What does linear algebra help to create better machine learning algorithms?
Answer 8: better supervised as well as unsupervised machine learning

Difficulty: Medium
Question 9: What is an example of supervised learning algorithms?
Answer 9: logistic regression linear regression decision trees

Difficulty: Medium
Question 10: What is an important department of mathematics that is easy to understand?
Answer 10: easy to learn linear algebra

Appendix B: Code

1. **Installation of Required Packages**

```
# Install necessary packages
!pip install transformers
!pip install pymupdf
!pip install pytesseract
!pip install pillow
!pip install huggingface_hub

# Install Tesseract OCR
!apt-get install -y tesseract-ocr
!apt-get install -y libtesseract-dev
```

2. Streamlit Application Code

```
with open('QAPair_Generator.py', 'w') as f:
    f.write("""
import streamlit as st
import tempfile
import fitz  # PyMuPDF
import pytesseract
from PIL import Image
import io
import os
import re
import torch
from transformers import T5ForConditionalGeneration, T5Tokenizer, RobertaTokenizer,
RobertaForSequenceClassification, pipeline
from huggingface_hub import login

# Initialize Streamlit app
st.title('QA Pair Generator')
st.markdown('<style>h1{color: orange; text-align: center;}</style>', unsafe_allow_html=True)
st.subheader('Generate Questions and Answers from Uploaded PDFs')

# File upload widget
uploaded_files = st.sidebar.file_uploader("Upload PDF files", type=["pdf"], accept_multiple_files=True)

# Authenticate with Hugging Face
api_key = "your_hugging_face_token"
login(token=api_key)

# Load the pre-trained Valhalla model and tokenizer for question generation
model_name = "valhalla/t5-small-qg-hl"
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
t5_model = T5ForConditionalGeneration.from_pretrained(model_name).to(device)
t5_tokenizer = T5Tokenizer.from_pretrained(model_name, legacy=False)

# Load the RoBERTa model and tokenizer for difficulty classification
classification_model_name = "roberta-base"
classification_tokenizer = RobertaTokenizer.from_pretrained(classification_model_name)
classification_model = RobertaForSequenceClassification.from_pretrained(classification_model_name).to(device)

# Function to extract text and images from PDF
def extract_text_and_images(pdf_path):
    doc = fitz.open(pdf_path)
    text_content = ""

    for page_num in range(len(doc)):
        page = doc.load_page(page_num)
        text_content += page.get_text()

        for img in page.get_images(full=True):
            xref = img[0]
            base_image = doc.extract_image(xref)
            image_bytes = base_image["image"]
            image = Image.open(io.BytesIO(image_bytes))
            # Extract text from image using Tesseract
            text_content += pytesseract.image_to_string(image)

    return text_content

# Function to clean extracted text
def clean_text(text):
    text = text.lower()
    text = re.sub(r'\s+', ' ', text)
    text = re.sub(r'[^\x00-\x7F]+', '', text)
    text = re.sub(r'[^a-zA-Z0-9\s.,!?]', '', text)
    return text.strip()

# Function to segment cleaned text into smaller chunks
def segment_text(text, max_words=100):
    words = text.split()
    segments = []
    current_segment = []
    current_length = 0

    for word in words:
        current_segment.append(word)
        current_length += 1
        if current_length >= max_words:
            segments.append(' '.join(current_segment))
            current_segment = []
            current_length = 0

    if current_segment:
        segments.append(' '.join(current_segment))

    return segments

# Function to generate questions from text segments
def generate_question(segment):
    input_text = f"generate questions from the following text: {segment.replace('</s>', '')}"
    input_ids = t5_tokenizer.encode(input_text, return_tensors='pt').to(device)
    outputs = t5_model.generate(input_ids, max_length=50, num_beams=5, early_stopping=True, do_sample=True)
    question = t5_tokenizer.decode(outputs[0], skip_special_tokens=True)
    return question

# Function to classify question difficulty
def classify_difficulty(question):
    inputs = classification_tokenizer(question, return_tensors='pt').to(device)
    outputs = classification_model(**inputs)
    logits = outputs.logits
    predicted_class = torch.argmax(logits, dim=1).item()
    # Assuming 3 classes: 0 = Easy, 1 = Medium, 2 = Hard
    difficulty = ["Easy", "Medium", "Hard"][predicted_class]
    return difficulty

# Function to extract answers from text segments
def extract_answer(question, context):
    qa_pipeline = pipeline("question-answering", model="deepset/roberta-base-squad2",
tokenizer="deepset/roberta-base-squad2")
    result = qa_pipeline(question=question, context=context)
    return result['answer']

if uploaded_files:
    all_texts = ""
    for uploaded_file in uploaded_files:
        with tempfile.NamedTemporaryFile(delete=False, suffix=".pdf") as temp_file:
            temp_file.write(uploaded_file.read())
            file_path = temp_file.name
            all_texts += extract_text_and_images(file_path) + " "
            os.remove(file_path)

    cleaned_text = clean_text(all_texts)
    segments = segment_text(cleaned_text)

    qa_pairs = []
    for segment in segments:
        question = generate_question(segment)
        difficulty = classify_difficulty(question)
        answer = extract_answer(question, segment)
        qa_pairs.append({'question': question, 'answer': answer, 'difficulty': difficulty})

    # Display QA pairs
    st.subheader("Generated QA Pairs")
    for idx, qa_pair in enumerate(qa_pairs, 1):
        st.write(f"**Difficulty:** {qa_pair['difficulty']}")
        st.write(f"**Question {idx}:** {qa_pair['question']}")
        st.write(f"**Answer {idx}:** {qa_pair['answer']}")
        st.write("---")
    """)
```

3. Run the Streamlit Application

```
from pyngrok import ngrok
ngrok.set_auth_token("your_ngrok_auth_token")

# Open a tunnel on port 8501 for streamlit
public_url = ngrok.connect(addr='8501', proto='http')
print(f'Public URL: {public_url}')

# Run the Streamlit app
!streamlit run QAPair_Generator.py --server.port 8501
```

Notes:

Ensure all required packages and Tesseract OCR are installed. Replace "your_hugging_face_token" and "your_ngrok_auth_token" with your actual Hugging Face API and Ngrok tokens. Use Ngrok to expose your local Streamlit app to the web. This setup will enable PDF uploads, processing, and QA pair generation via the Streamlit interface.