

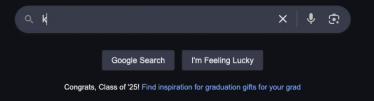
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Motivation

- Students often need to click through multiple university webpages to find basic information like deadlines, forms, or policies.
- Large language models can help, but struggle with accuracy without being tailored to the domain.
- Fine-tuning an LLM on universityspecific content enables faster, more reliable answers with less user friction.



Project Overview

Scraped content from approximately ten KU-affiliated subdomains and filtered meaningful information from raw HTML.

Training workflow of fine-tuning LLaMA 3.2 using LoRA and the PEFT framework, including prompt design, training configuration

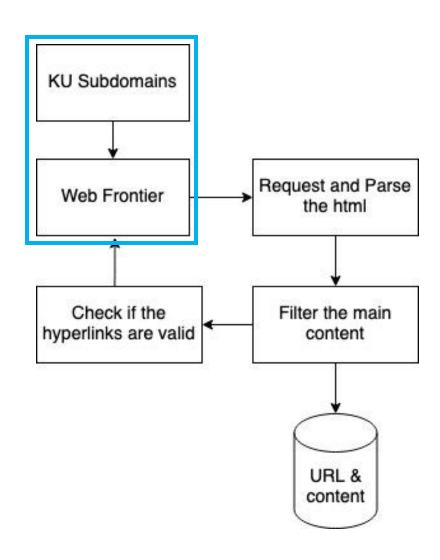
Raw Data Extraction Generating QAC pairs

Model Finetuning Model Evaluation

Leveraged the GPT-4o-mini model via the OpenAI API to automatically generate question, answer, and context triplets from the extracted content.

Evaluated model outputs based on overlap with reference answers, fluency of phrasing, and semantic similarity.

Raw Data Extraction



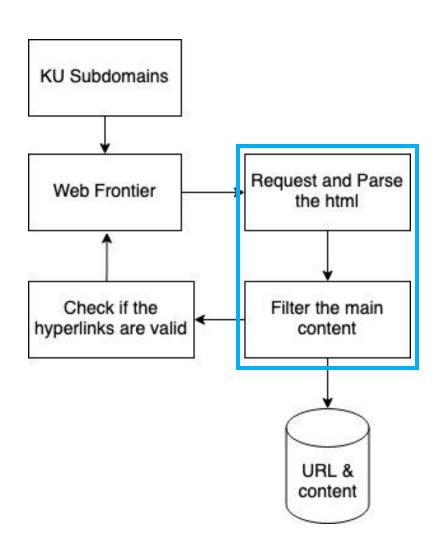
KU Subdomains and Web Frontier

- Selected some KU-affiliated subdomains containing information on engineering programs, international student services, research, etc.
- Used a curated list as the seed input for crawling.

Web Frontier

- Basically, a double ended queue that stores
 URLs to be visited
- Ensures breadth first crawl.

Raw Data Extraction



Request and Parse the HTML

• Send HTTP request and parse the HTML using BeautifulSoup to extract all the readable data.

Filter the main content

- Extract content only from the "main" section of the page.
- Clean the data removing HTML tags, special characters, whitespace, etc.
- Count the num of tokens and store the cleaned data as URL, content, and num_tokens.

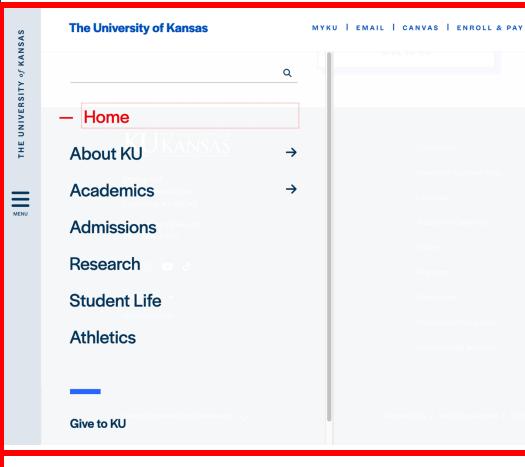




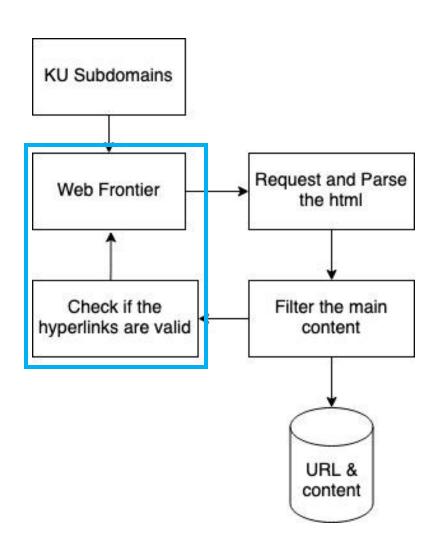


GIVE TO KU





Raw Data Extraction



Check for hyperlinks

- Extract all the hyperlinks from the HTML.
- Check if the links are valid KU subdomain, not previously visited, not a redirect (login, returnto, etc.)
- Append links to the web frontier.

Raw Data Example

```
"url": "https://iss.ku.edu/f-1-cap-gap",
   "text": "Cap Gap Extension The cap gap extension is a period in which an eliqible F-1
student\u2019s status is ...",
   "num tokens": 886},
   "url": "https://iss.ku.edu/f-1-economic-hardship",
   "text": "Employment Based on Severe Economic Hardship F-1 students may be eligible if
they have demonstrated severe economic hardship (SEH), to apply ... ",
   "num tokens": 887},
   "url": "https://app.eecs.ku.edu/mill/emailform.php",
   "text": "This Page has moved! This page has moved! Please update your links ...
   "num tokens": 62},
```

Generating QAC pairs and Final Dataset

- Converted raw data into pairs of Question, Answer, and Context.
- Used GPT-4o-mini via OpenAl API to automatically generate question-answer-context (QAC) triples.
- Initial prompt versions led to issues:
 - Duplicate or irrelevant questions
 - Invalid JSON formatting
 - Answers not grounded in context
- Refined the prompt iteratively to improve quality and formatting.
- Generated ~4,380 QAC pairs from ~5,600 pages; excluded low-value pages (e.g., people.ku.edu).
- Final dataset contains good-quality, sourcelinked QAC pairs, essential for effective finetuning.

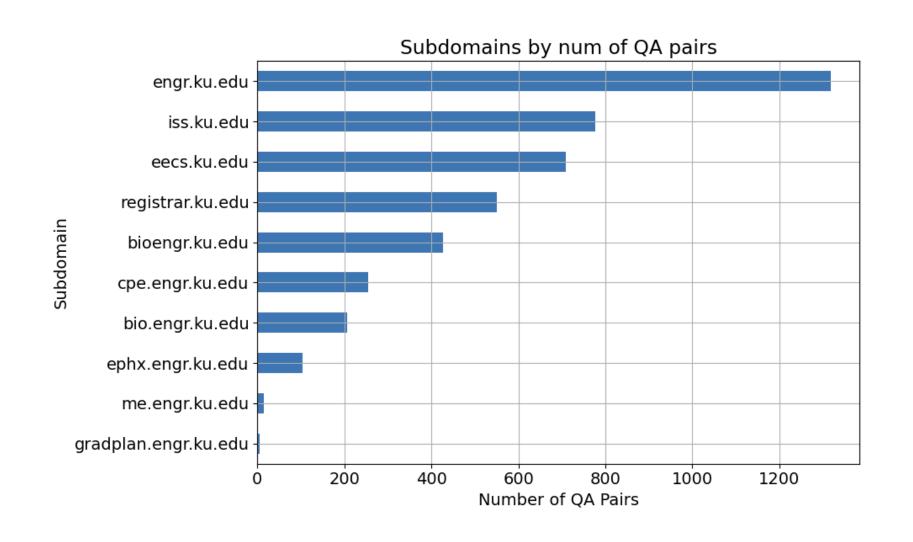
	num rows	% rows
Training	3066	70%
Validation	438	10%
Testing	876	20%
Total	4380	100%

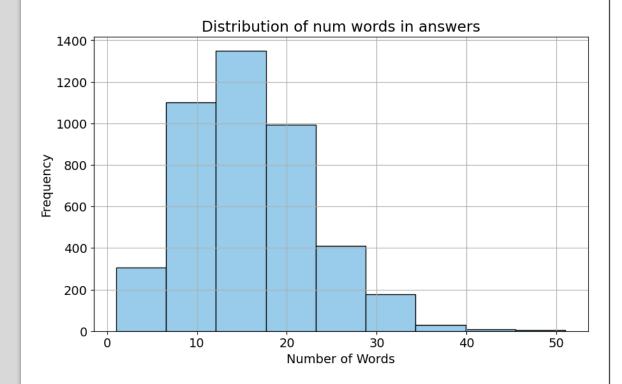
Table 1: Train-test split of the dataset

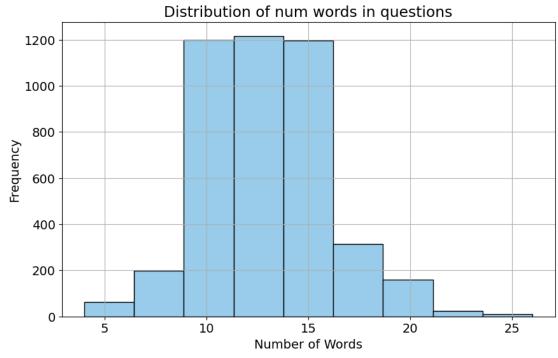
	Max	Min	Avg
Question	26	4	12.87
Answer	51	1	16
Context	106	1	22.71

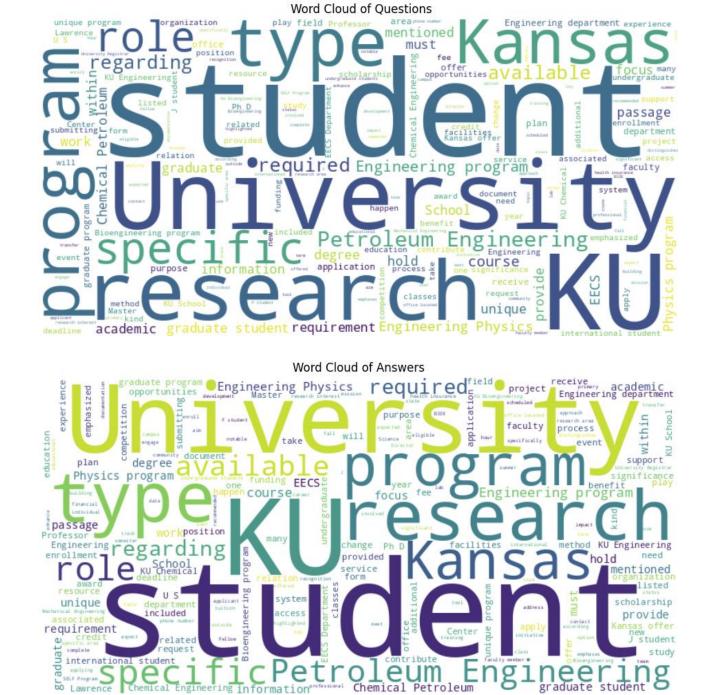
Table 2: Number of words in QAC pairs

Understanding the Dataset









Some good examples of QAC pairs

```
"question": "What specific requests can be reviewed during a Drop-In Advising session?",
    "answer": "During Drop-In Advising, the following iHawk requests can be reviewed and
processed if they are completely submitted: Reduced Course Load (F-1 or J-1), Add Dependents (F
or J), Financial Update on I-20, among others.",
   "context": "The following iHawk requests can be reviewed and processed during drop-ins/walk-
ins...",
    "source": "https://iss.ku.edu/advising"},
    "question": "What does 'D/S' on your I-94 signify?",
    "answer": "'D/S' stands for 'Duration of Status', meaning you are admitted to the U.S. for as
long as you are maintaining your status.",
    "context": "You should have the letters 'D/S' on your I-94, which means that you are admitted
to the U.S. for the 'Duration of Status', or for as long as your are maintaining status - this is
typically the time that it takes for you to complete your degree/program.",
    "source": "https://iss.ku.edu/i94-newly-admitted"
```

Some bad examples of QAC pairs

```
"question": "How many new international students arrived at KU this fall?",
    "answer": "Over 400 new international students arrived this fall.",
    "context": "400+ new international students arrived this fall",
    "source": "https://iss.ku.edu"},
    "question": "What is required to change, release, or withhold certain information aside from contact
details?",
    "answer": "A form must be submitted to the office to change, release, or withhold other information.",
    "context": "...the change, release, or withholding of other information requires a form be submitted to our
office.",
    "source": "https://registrar.ku.edu/student-records"},
    "question": "What type of bank account should your ATM card be tied to?",
    "answer": "ATM cards should be tied to a checking account, not a savings account.",
    "context": "ATM cards should be tied to a checking (not savings) account.",
    "source": "https://iss.ku.edu/finances-newly-admitted"},
```

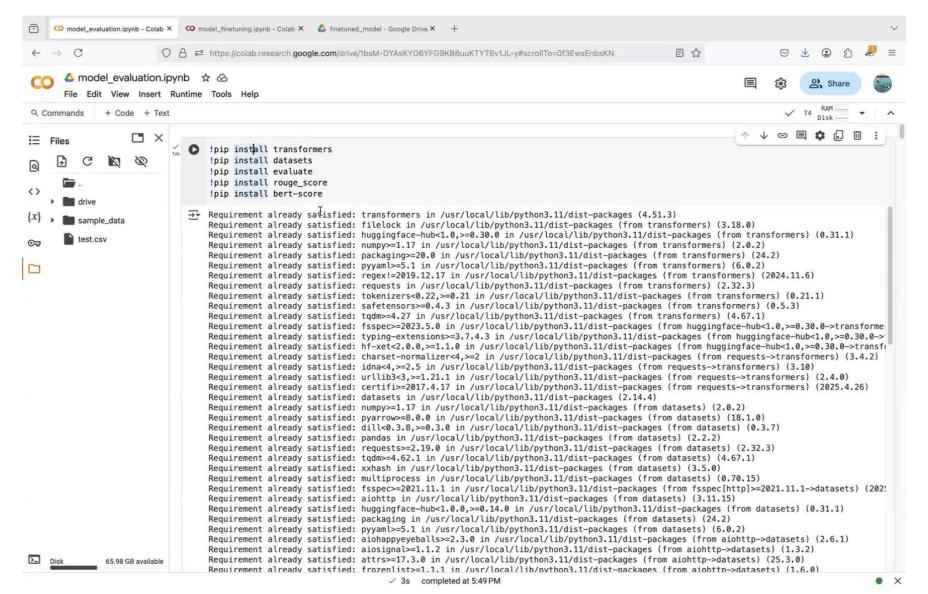
Training Workflow

- Model meta-llama/Llama-3.2-1B-Instruct from Hugging Face
- Used Parameter-Efficient Fine-Tuning (PEFT) with Low-Rank Adaptation (LoRA) to update only 1.79% (~22.5M) of model parameters.
- Targeted layers for LoRA:
 - Self-attention: q_proj, k_proj, v_proj, o_proj
 - MLP: gate_proj, up_proj, down_proj
- Applied 4-bit quantization (nf4 precision, bfloat16 compute) via BitsAndBytes for memory efficiency—trained on a single T4 GPU.
- Used Hugging Face's AutoModelForCausalLM with resized token embeddings and automatic device mapping.
- Used the SFTTrainer from trl library to train the model.
- Loss function: Cross-Entropy, applied only to the model's answer using DataCollatorForCompletionOnlyLM

```
LlamaForCausalLM(
  (model): LlamaModel(
    (embed_tokens): Embedding(128264, 2048)
    (layers): ModuleList(
      (0-15): 16 x LlamaDecoderLayer(
        (self_attn): LlamaAttention(
          (q_proj): Linear4bit(in_features=2048, out_features=2048, bias=
          (k_proj): Linear4bit(in_features=2048, out_features=512, bias=F
          (v_proj): Linear4bit(in_features=2048, out_features=512, bias=F
          (o proj): Linear4bit(in features=2048, out features=2048, bias=
        (mlp): LlamaMLP(
          (gate_proj): Linear4bit(in_features=2048, out_features=8192, bi
          (up_proj): Linear4bit(in_features=2048, out_features=8192, bias
          (down_proj): Linear4bit(in_features=8192, out_features=2048, bi
          (act fn): SiLU()
        (input_layernorm): LlamaRMSNorm((2048,), eps=1e-05)
        (post attention layernorm): LlamaRMSNorm((2048,), eps=1e-05)
    (norm): LlamaRMSNorm((2048,), eps=1e-05)
    (rotary_emb): LlamaRotaryEmbedding()
  (lm head): Linear(in features=2048, out features=128264, bias=False)
```



Inference Demo



Evaluation Setup

- Base model is the original model not trained on KU's dataset.
- Finetuned model is basically base model trained on KU's dataset.
- Both the models were tested in two settings without context and with context.
- Apart from manual checks, we evaluated the model outputs on
 - BERT Score
 - ROUGE Score
 - BLEU Score

Testing Prompts Examples

With Context

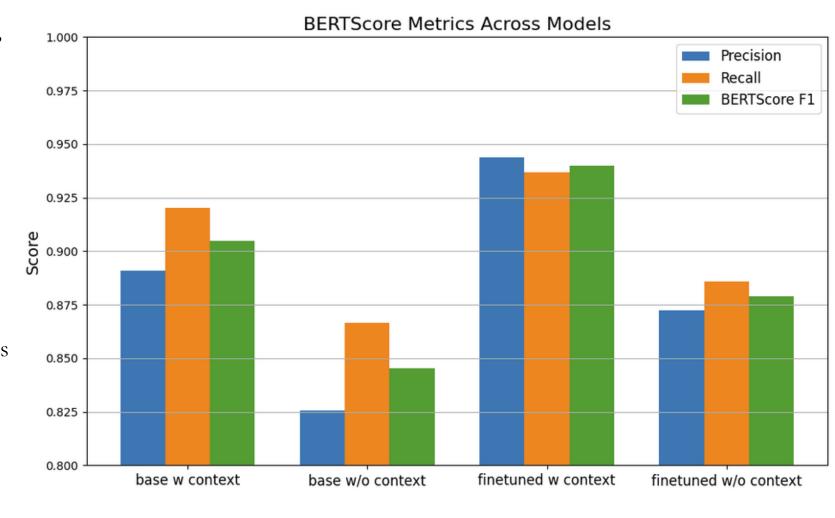
```
... Use only the information to
answer the question<|eot id|>
<|start header id|>user<|end hea
der id|> What should
international students with F-1
or J-1 status do if they need to
change their name on university
records?
Information: ``` International
students with an F-1 or J-1
status must contact
International Student Services
at (785) 864-3617 to change the
name on your I-20 or DS-2019.
  `<|eot id|><|start header id|>
assistanT<|end header id|>
```

Without Context

```
...You are a helpful
assistant<|eot_id|>
<|start_header_id|>user<|end_header_id|> What should
international students with
F-1 or J-1 status do if they
need to change their name on
university records?
<|eot_id|><|start_header_id|>
assistant<|end_header_id|>
```

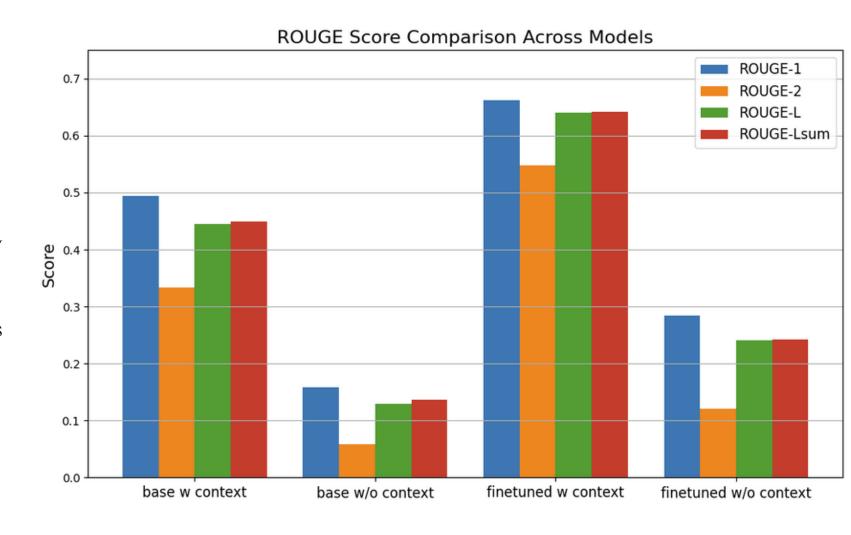
BERT Score – Semantic Similarity

- BERTScore, a more recent metric, uses contextual embeddings from pre-trained language models like BERT to compute semantic similarity between the generated answer and the actual answer.
- Without context
 - The finetuned model significantly outperforms the base model by about 5%.
- With context
 - The finetuned model achieves about 4% better F1 score than the base model, indicating that it produces answers semantically closest to the actual answers.



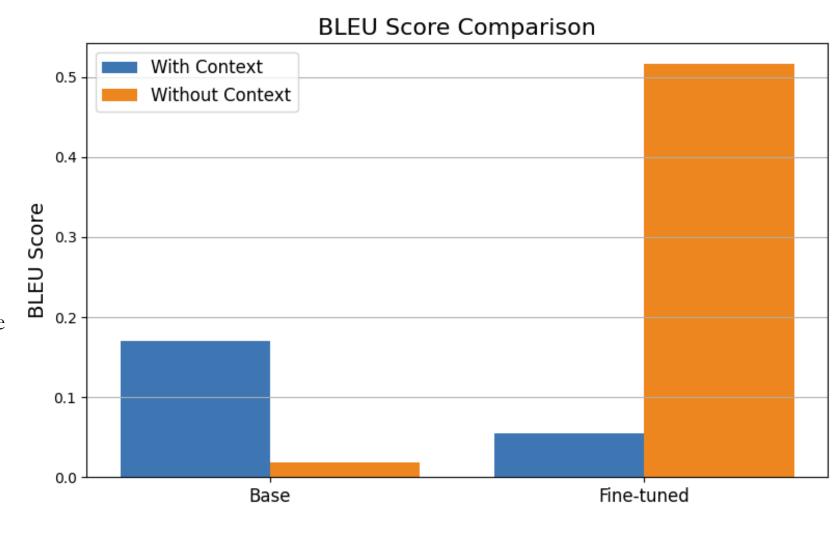
ROUGE Score – recall based n-gram overlap

- It measures how much of the actual answer matches the generated answer.
- Recall based penalizes missing information from the answer.
- Without context
 - Finetuned model outperforms base model by about 2x across all score.
- With context
 - Finetuned model performs significantly better than the base model.



BLEU Score – precision based n-gram overlap

- It measures how much of the generated answer matches the actual answer.
- Precision based penalizes extra information in the answer.
- Without context
 - Finetuned model outperforms the base model by a much large factor
- With context
 - Base model outperforms the finetuned model by almost 3x.



Conclusion

- Developed a KU-specific question-answering system by extracting data from KU webpages and finetuning Llama 3.2.
- Observed significant improvements in the model's ability to generate accurate responses, especially in no-context settings.
- Finetuned model mostly preformed better across BLEU, ROUGE, and BERTScore metrics showed consistent gains across both lexical and semantic metrics.
- Demonstrated that even small, high-quality domain-specific datasets can effectively enhance language model performance.

Limitations and Future Work

- One major limitation we observed during this project was that the presence of low-quality or noisy QAC pairs in the dataset.
 - This could be improved by adding a data quality check to the pipeline based on filtering techniques based on token length, semantic similarity, or sentence embeddings to improve alignment in QAC pairs.
- It would also be better to have a domain specific benchmark dataset for evaluation than cross validation.
- A larger number of high-quality QAC pairs would likely improve model performance and generalization.
- Automate the data pipeline using tools like Airflow, AWS EC2, and S3 for scalable and repeatable data extraction.
- Evaluate the model in user-facing applications to assess real-world usability and feedback.

