



CryptoLLM

Large Language Models for Cryptography Assistance

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Motivation - LLMs and Mathematics

- Suboptimal performance of LLMs in mathematical reasoning task [1] [2]
- Arithmetic problems have a single solution with multistep reasoning.
- Recent LLMs perform well for low-difficulty mathematics but suffer in medium and higher-difficulty challenges [3; 4; 5].



Motivation - Why cryptographic LLMs?

- Cryptography is essential for secure information and transactions.
- Cryptography is a complex field that requires a strong foundation in mathematics and computer science.
- · Cryptography is one of the most difficult fields to learn.
- There exist no AI assistants, only limited mathematical tools.



Motivation - Why cryptographic LLMs?

® '

You

what is dishonest majority in cryptography?



ChatGPT

I'm not aware of a specific term or concept called "dishonest majority" in cryptography. It's possible that there might be a misunderstanding or a miscommunication of the term. Cryptography involves the study of secure communication techniques, and concepts like trust, honesty, and security play crucial roles in this field.

If you have a specific context or if there's a different term you're referring to, please provide more details, and I'll do my best to assist you. Alternatively, if it's a newer concept or terminology that has emerged after my last training data in January 2022, I might not be aware of it.



ls 2+2+22+222+2=300?



Let's add the numbers:

2+2+22+222+2=250

So, 2+2+22+222+2 equals 250, not 300.



Is 02+2+22+0222+2=300?



Let's add the numbers:

02 + 2 + 22 + 0222 + 2 = 220

So, 02 + 2 + 22 + 0222 + 2 equals 220, not 300.



Problem Statement

We aim to develop:

- CryptoLLM an LLM assistant for cryptographic problems using language chaining and fine-tuned model.
- · Crypto dataset collection to train the LLM.



Figure: Language Chaining Illustration



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Flowchart Design

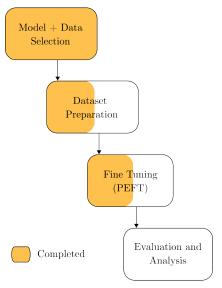




Figure: Methodology of the design

Fine-tuning LLMs - Model Selection

- · Llama-2-Chat 7B model [6]
 - · Open Source
 - At par in some criteria with popular closed-source models like ChatGPT [7] and PaLM [8].
 - · Proven results for basic math datasets [9]
 - Reasonable compute requirements for fine-tuning 28GB GPU for full precision (7B model)
- Mistral 7B [10] and CodeLlamma[11] will be tested parallelly for results.



Dataset Preparation: 1- Task and Scope

- Main cryptographic primitives:
 - · Number Theory
 - · Symmetric Cipher Model
 - · Block Ciphers
 - · Finite Fields
 - · Random Bit Generation and Stream Ciphers
 - · Asymmetric Ciphers... etc.



Dataset Preparation: 2- Data Collection and Source

- · Well-established academic textbooks
 - · Cryptography and Network Security, William Stallings [12]
 - · Number Theory and Cryptography, Neal Koblitz [13]
 - A Gentle introduction to number theory and cryptography, Luis Finotti [14]
 - · Mathematics Aptitude Test of Heuristics (MATH) [15]



Dataset Preparation: 3- Cleaning and Preprocessing Data

- Tokenization
- Standardization
 - · Numerical form in latex common standard.
 - · Chain of thought approach [16]
- · Monolingual Data English only
- Manual Inspection



Dataset Preparation: 4- Annotation

- · Labels: for a good train-test split and markers
 - question
 - answer
 - type: word or math
 - · category: orig or back
 - · topic: numbertheory or cipher
- · Manual Annotation (using prompt engineering in gpt-3.5)
- Initial target: 1k samples



Dataset Preparation: 5- Augmentation

- · Backward vs. Forward reasoning answers [17]
 - Deduce missing values in question
 - · Only numerical masks no phrase mask
- Input Space Augmentation



Dataset Preparation: 6- Data Format Conversion

```
<s>[INST] <<SYS>>
{{ system_prompt }}
<</SYS>>
{{ user_message }} [/INST]
```

- Ensures high-quality dataset
- Other styles include ChatML and Alpaca style prompt formatting.



Fine Tuning Flowchart

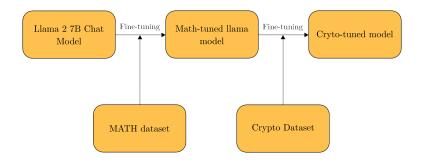




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Dataset Samples

- · 300/1000 samples prepared till now
- Sample data(csv file):
 question, answer, type, category, topic, source

"Use the Euclidean Algorithm to compute the GCD of the following numbers: \$300\$ and \$222\$", "To compute the GCD of \$300\$ and \$222\$ using the Euclidean Algorithm, we perform a series of divisions: $$300 = 222$ \cdot 1 + 78$$, $$222 = 78$ \cdot 2 + 66$$, $$78 = 66$ \cdot 1 + 12$$, $$66 = 12$ \cdot 2 + 66$$, $$12 = 6$ \cdot 2 + 0$$. The last non-zero remainder is \$6\$. Therefore, the GCD of \$300\$ and \$222\$ is \$6\$.", orig, math, numbertheory, grad.pdf



Fine Tuning on MATH (in progress)

- · Parameter efficient fine tuning (PEFT) [18; 19].
- · 12GB GPU RAM for 7B parameter model
- paged-adamw-32bit optimizer
- Supervised Fine Tuning (SFT)
- · 7.5k samples of basic (high school level) math problems



Challenges

- Fine Tuning
 - · Massive Compute Requirements:
 - · QLoRA [20]: 1x A100 (80GB GPU) or 2x RTX 3090
 - Full fine-tuning: 16x A100s
- Dataset Preparation
 - Manual inspection for verifying correctness of computations
 - Scarcity of documented solutions (to relevant numerical problems)



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Goals

- · Complete crypto-dataset
- · Crypto fine-tuned model
- · Analysis on language chaining vs. fine-tuned model
- · Analysis on prompt engineering vs. fine-tuning model output



Timeline

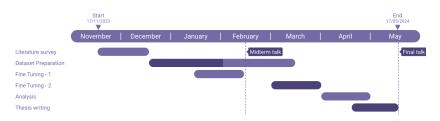


Figure: Timeline of the project



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Thank you!

