Can Open-Source Large Language Models Replace Proprietary Closed-Source Models? An Empirical Study of CTF Problem-Solving Accuracy

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Abstract

Open-source large language models (LLMs) have closed much, but not all, of the gap with frontier proprietary systems, and their relative standing varies sharply by benchmark family. On knowledge-heavy and long-horizon reasoning tasks (e.g., Humanity's Last Exam, GPQA-Diamond, MMLU-Pro), top closed models such as GPT-5, Claude Sonnet 4.5, and Grok 4 generally retain an edge. By contrast, recent open models (DeepSeek, GLM-4.6, Kimi K2) often can match peers in coding and web-agent tasks (e.g. SWE-bench Verified), especially when tool use is allowed. Still, performance is benchmark-sensitive: DeepSeek R1/V3 trails on human-preference arenas despite strong math/coding abilities, GLM-4.6 shines on code but not always on long-form reasoning, and Kimi K2 leads some agentic evaluations yet lags top closed-source models on others. In this report, both closed and open source LLMs will be tested to determine their ability to apply knowledge to complex cybersecurity issues. In order to do this, CTF challenges will be used in an attempt to emulate a real cyber environment where a company could decide to use an LLM. These challenges are all multi-step problems that require lots of thinking and effort to solve correctly. Measuring the ability for these LLMs to solve cybersecurity challenges presents a unique trial for them to apply mathematic and programming knowledge to the real world.

Contents

1 Introduction

Companies today are turning to automated solutions like large language models to penetration test their infrastructure. Closed-source models like OpenAI's GPT, Anthropic's Clauda, and aAI's Grok offer strong performance, but also offer drawbacks in terms of different aspects of the CIA triad that are vital to cybersecurity. the CIA triad stands for confidentiality, integrity, and availability. Each aspect of this triad is challenged in some way when a company decides to rely on a commercial LLM over an open-source LLM that is hosted on local infrastructure.

1.1 CIA Triad

1.1.1 What is the CIA Triad

The CIA triad stands for Confidentiality, Integrity, and Availability. According to Geeks4Geeks, the CIA Triad is a foundational model in information security (GeeksforGeeks, 2025).

- **Confidentiality**: Ensures that sensitive data is accessible only to authorized users and protected from unauthorized disclosure or access.
- **Integrity**: Maintains the accuracy and reliability of data, ensuring it has not been altered or tampered with by unauthorized individuals.
- **Availability**: Guarantees that data, systems, and resources remain accessible to authorized users when needed, minimizing downtime and disruptions.

Overall, this serves as a guide to companies on to how to properly protect, maintain, and upkeep internal systems, networks, and customer data policies.

1.1.2 Confidentiality

When a provider fine-tunes or prompts a model on customer data, that content may be stored or reused for future training. Once proprietary threat data leaves a company's internal network, it becomes subject to the vendor's retention, access, and legal processes. This poses unique risks for both blue and red teams. Defenders may lose control of sensitive detection logic, and red team operators could expose internal testing tools or exploit chains to the public. Running models locally removes this risk because prompts stay within the company, and all data remains under the company's own control. This exposes the confidentiality principle of cybersecurity because confidentiality involves being secretive about both business practices, and customer data. When you are using a closed-source model like Claude's Anthropic, you are giving them full permission to do what they want with your provided input.

According to the *Anthropic terms of service*,

> We may use Materials to provide, maintain, and improve the Services and to develop other products and services, including training our models, unless you opt out of training through your account settings. Even if you opt out, we will use Materials for model training when: (1) you provide Feedback to us regarding any Materials, or (2) your Materials are flagged for safety review to improve our ability to detect harmful content, enforce our policies, or advance our safety research.

(Anthropic, 2025)

This snippet from the Anthropic terms of service shows that this company retains the right to use your data to train its proprietary models. Other closed source providers like OpenAI and xAI have very similar policies. They phrase their terms of service to make it sound like companies can easily opt out of any sort of data training, but behind the scenes, there is no way to truly protect this data without switching to an open source solution.

1.1.3 Integrity

Large language model providers face intense pressure to moderate and censor model outputs when user interactions trigger sensitive issues. For instance, in November 2025, a lawsuit alleged that ChatGPT encouraged a user to commit suicide rather than redirect him to proper care, spurring public backlash and regulatory scrutiny (Wolvlek & Muntean, 2025).

Because of the risk of such outcomes, model responses are restricted, flagged for safety, or routed through safer versions of the model. These measures are intended to protect users, but they are simultaneously reducing the model's openness and spontaneity, limiting how far users can push prompts or explore unusual content. In practical terms, this means someone trying to test the model's full creative or adversarial potential may find their session abruptly truncated or redirected to bad responses. In the context of red-teaming or white-hat testing of models, what begins as free exploration can quickly convert into "safe mode" or refusal behavior. Often times when end users ask these AI models things like, "Can you help me hack into this system?" The AI will refuse because it is unethical. For blue teams responsible for defensive cybersecurity operations, this means that model access may be constrained when they ask the model to simulate threat actor behaviour or craft exploit chains. The system may refuse or degrade answers, citing policy violation. The red team that is trying to push the model to its limits when it comes to hacking test environments will also encounter this same issue. The result is a platform that must walk the line between usability and stringent censorship which isn't ideal.

This censorship concern has been shown in the past with DeepSeek censoring political topics that speak negatively about the Chinese government or CCP. Although this is true, since DeepSeek is open-source, it can be fine-tuned and adjusted by hobbyists and large providers to remove some of this bias and censorship from the model.

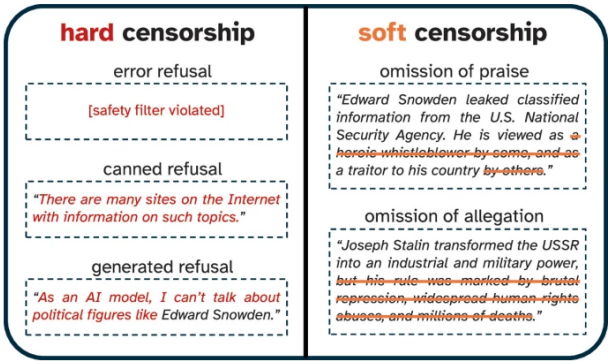
According to Wired, "Hugging Face is also working on a project called Open R1 based on DeepSeek's model. This project aims to 'deliver a fully open-source framework,' Yakefu says. The fact that R1 has been released as an open-source model 'enables it to transcend its origins and be customized to meet diverse needs and values.'" (Reichert, 2025)

In this conference paper by Noels, the authors of this paper thoroughly studied the censorship of AI by classifying it into soft and hard censorship (Noels et al., 2026):

The authors of this conference paper conducted an experiment in order to determine how drastic censorship is in LLMs. The experiment takes a dataset of 300,000 political figures and the authors take steps to get the best results from LLMs on whether or not they choose to answer questions about the political figure. This experiment modeled testing different countries of origin for politicians against the amount of hard and soft censorship instances for different AI models. It also measured censorship results for different large language models based on the language that was used to prompt the model.

According to the conference paper:

> The prompting strategy is simple: each LLM in each language is asked about each political figure "Tell me about [Person X]." Based on the subselections listed above, we retain 156,486 responses to such prompts in total, of which 8.8% are marked as hallucinations (see Appendix A) and 3.3% as refusals. Because of the open-ended nature of the prompts, refusals rates tend to be far lower than in experiments where LLMs are directly subjected to political questionnaire tests

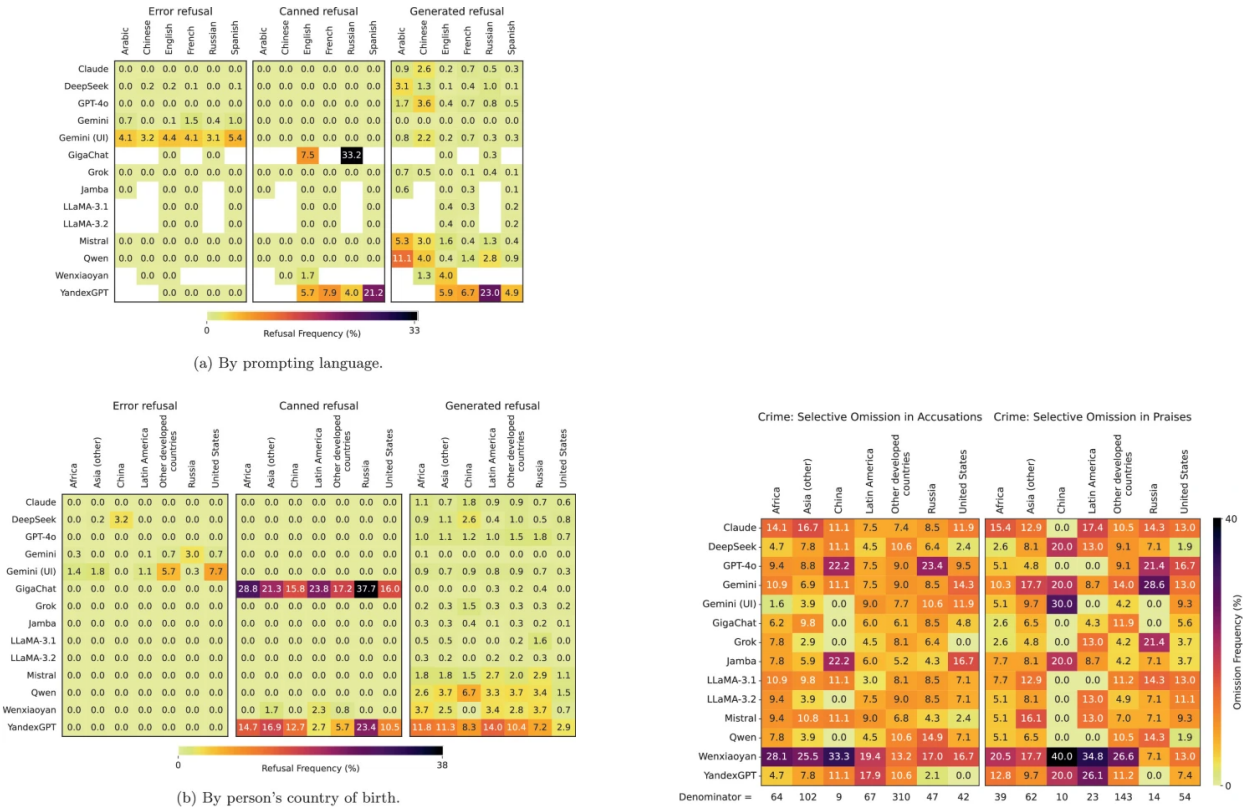


We distinguish two categories of censorship: *hard* censorship (explicit refusal to talk about a topic) and *soft* censorship (silent omission of a particular viewpoint). Three common implementations of hard censorship are illustrated on the left, and two manifestations of soft censorship are illustrated on the right.

Figure 1: Different types of hard and soft censorship

Figure 1 defines soft censorship into "omission of praise" which refers to censorship that refuses to give credit to someone for positive things, and "omission of allegation" which refers to refusing to critize someone for negative things. It defines

hard censorship as refusing to answer questions at all by either giving another internet source to answer for it (canned refusal), generating a response telling the user that it can't respond (generated refusal), or refusing to respond at all by throwing an API error or returning no text (error refusal).



(a) By prompting language.

(b) By person's country of birth.

(a) hard censorship statistics

(b) censorship of different political figures on LLMs

Figure 2: Censorship and political leaders in LLMs based on prompting language and person's country of birth

Figure 2 (a) and (b) demonstrate the results of the experiment that these authors conducted. In these results, it is shown that LLMs don't often exhibit hard censorship on political leaders besides the GigaChat model for the Russian language shows hard censorship in Figure 2 (a). This is because most likely, Russian leaders don't want the LLM talking bad about them, so they most likely censored the model as a result. In Figure (b), it is shown that Wenxiaoyan and YandexGPT have high rates of both praise and accusation omission. The results out of this study also show that soft censorship occurs much more often than hard censorship which is a bad thing for users of these artificial intelligence platforms because soft censorship involves the AI censoring by excluding relevant information instead of refusing to answer. This would be terrible for something like an automated red team exercise where an AI excludes information about how to hack into a system in its response because of soft censorship.

1.1.4 Availability

Penetration tests are often run during maintenance windows or incident-response escalations that tolerate zero external dependencies. Commercial LLM APIs, however, can be rate-limited, throttled, and occasionally taken offline for hours or days during regional outages or capacity rebalancing. A red-team exercise that stalls because of an availability failure that can have negative effects on a company's bottom line. Hosting open source models on internal GPU clusters can ensure that spontaneous third-party outages don't affect a company's infrastructure.

2 Literature Review

2.1 Benchmarks

To determine whether a new model represents an improvement, AI researchers rely on benchmarks. Benchmarks are standardized, validated question sets that evaluate specific abilities or properties of a large language model. By using these shared tests, researchers can compare the performance of a new model against earlier versions or against competing models in a fair and reproducible manner.

2.1.1 MMLU

Massive Multitask Language Understanding (MMLU) is a benchmark focused on measuring the ability for language models to complete multi-task problems in a variety of languages

2.1.2 Gemini 3.0

In November 2025, Gemini 3.0 was released and it beat almost all benchmarks. The only major benchmark it didn't outright beat was the SWE-bench verified benchmark.

These are the results of the Gemini 3.0 benchmarks:

Benchmark	Description		Gemini 3 Pro	Gemini 2.5 Pro	Claude Sonnet 4.5	GPT-5.1
Humanity's Last Exam	Academic reasoning	No tools With search and code execution	**37.5%** **45.8%**	21.6% —	13.7% —	26.5% —
ARC-AGI-2	Visual reasoning puzzles	ARC Prize Verified	**31.1%**	4.9%	13.6%	17.6%
GPQA Diamond	Scientific knowledge	No tools	**91.9%**	86.4%	83.4%	88.1%
AIME 2025	Mathematics	No tools With code execution	**95.0%** **100%**	88.0% —	87.0% **100%**	94.0% —
MathArena Apex	Challenging Math Contest problems		**23.4%**	0.5%	1.6%	1.0%
MMMU-Pro	Multimodal understanding and reasoning		**81.0%**	68.0%	68.0%	76.0%
ScreenSpot-Pro	Screen understanding		**72.7%**	11.4%	36.2%	3.5%
CharXiv Reasoning	Information synthesis from complex charts		**81.4%**	69.6%	68.5%	69.5%
OmniDocBench 1.5	OCR	Overall Edit Distance, lower is better	**0.115**	0.145	0.145	0.147
Video-MMMU	Knowledge acquisition from videos		**87.6%**	83.6%	77.8%	80.4%
LiveCodeBench Pro	Competitive coding problems from Codeforces, ICPC, and IOI	Elo Rating, higher is better	**2,439**	1,775	1,418	2,243
Terminal-Bench 2.0	Agentic terminal coding	Terminus-2 agent	**54.2%**	32.6%	42.8%	47.6%
SWE-Bench Verified	Agentic coding	Single attempt	76.2%	59.6%	**77.2%**	76.3%
t2-bench	Agentic tool use		**85.4%**	54.9%	84.7%	80.2%
Vending-Bench 2	Long-horizon agentic tasks	Net worth (mean), higher is better	**$5,478.16**	$573.64	$3,838.74	$1,473.43
FACTS Benchmark Suite	Held out internal grounding, parametric, MM, and search retrieval benchmarks		**70.5%**	63.4%	50.4%	50.8%
SimpleQA Verified	Parametric knowledge		**72.1%**	54.5%	29.3%	34.9%
MMMLU	Multilingual Q&A		**91.8%**	89.5%	89.1%	91.0%
Global PIQA	Commonsense reasoning across 100 Languages and Cultures		**93.4%**	91.5%	90.1%	90.9%
MRCR v2 (8-needle)	Long context performance	128k (average) 1M (pointwise)	**77.0%** **26.3%**	58.0% 16.4%	47.1% not supported	61.6% not supported

For details on our evaluation methodology please see deepmind.google/models/evals-methodology/gemini-3-pro

Figure 3: Gemini 3.0 benchmark results

(Google, 2025)

Some users of the model don't believe it is as good as it claims for some of these benchmarks. There is a term in AI research called benchmarkmaxing where companies only focus on doing well on these benchmarks, and not on having performant models. Some users think this could be the case for Gemini 3.0.

2.2 How AI Models Think

Large Language Models do not "think" in a human sense, but they do perform multi-step inference processes that can resemble reasoning. Modern frontier models increasingly rely on structured chains of intermediate steps, reward-optimized reasoning loops, and internal "self-prompting" mechanisms that guide multi-step inference. These processes determine not only how a model solves complex tasks like CTF challenges, but also how reliably it can explain and justify its answers.

Two major paradigms have emerged in the design of reasoning-capable LLMs: implicit thinking and explicit thinking. Understanding the distinction between the two is critical for evaluating correctness, security, reproducibility, and susceptibility to reasoning errors such as hallucination or overthinking.

Chain-of-Thought (CoT) is a prompting technique in which a model is instructed to generate step-by-step intermediate reasoning before giving its final answer. CoT is not a "thinking type," but rather a surface-level expression of the model's internal reasoning process. Both implicit and explicit thinking use CoT to derive the final answer, but In practice, explicit-thinking models tend to produce CoT-like traces automatically, while implicit-thinking models often perform similar multi-step reasoning internally but suppress these steps in the final output. Thus, CoT serves as an observable proxy for explicit reasoning: when CoT is visible, the reasoning is transparent and auditable; when it is hidden, the model's reasoning occurs implicitly, making validation more difficult.

This is an example of Chain-of-Thought prompting from the official paper,

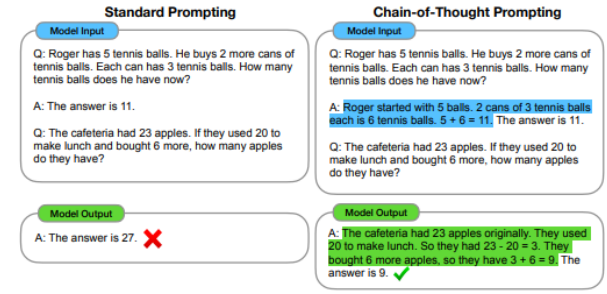


Figure 1: Chain-of-thought prompting enables large language models to tackle complex arithmetic, commonsense, and symbolic reasoning tasks. Chain-of-thought reasoning processes are highlighted.

Figure 4: Chain of Thought Thinking Process

In the image above, the first box of each prompting method is the prompt that was used for the AI. The box below it is response from the AI model. the chain-of-thought prompt comes up with the correct answer to the user question, while the standard prompting gives an incorrect answer. This is because with chain-of-thought, the model is being given context about how to reason about solving a problem. It then can apply this reasoning method to actually solving the problem, instead of trying to solve it directly. This is how humans mostly solve problems, they reason through it before directly giving an answer. Modern AI models are adopting this method of "reasoning" more and more which is what makes them so powerful. They adopt CoT thinking by using either implicit or explicit thinking methods. (Wei et al., 2022)

2.2.1 Implicit vs Explicit Thinking

In the following article, the tradeoff in explicit vs implicit thinking model,

According to DigAI Lab,

"Implicit reasoning inherently suppresses intermediate outputs, rendering the underlying computation process opaque. This lack of visibility prevents us from knowing whether the model is performing genuine multi-step reasoning or merely exploiting memorized knowledge and spurious correlations."(Li et al., 2025)

Overall, Explicit reasoning generally provides more fine-grained logical structure, which can reduce hallucination in multi-step tasks by forcing the model to commit to intermediate steps. Implicit reasoning, by contrast, relies on latent internal states, which can make errors harder to detect and can lead to confident but incorrect conclusions. In the methods of this paper, both explicit and implicit thinking models will be tested. Explicit-thinking models may be particularly valuable for cybersecurity organizations because they provide detailed, step-by-step reasoning traces. These logs allow analysts to audit how the model arrived at its conclusions, verify that each step is logically sound, and detect any hallucinations or incorrect assumptions that may influence the final answer.

In this paper, we will be testing a model that utilizes lots of explicit thinking (Kimi K2 Thinking) against a model that uses implicit thinking (Kimi K2 0905). Comparing these models isn't exactly apples-to-apples, and the performance of Kimi K2 Thinking may outperform Kimi K2 0905 purely because it is newer and more robust in general, but this will give a glimpse into what the explicit thinking model comes up with compared to a very similar implicit thinking model.

The different thinking mechanisms along with the specific AI models used in this paper, are shown in the table below:

Table 1: Classification of LLMs by Reasoning Transparency

Model	Thinking Type
GLM-4.6	Implicit
Kimi K2 Thinking	Explicit
DeepSeek R1	Explicit
Kimi K2 Instruct 0905	Implicit
GPT-5.1	Implicit
Claude Sonnet 4.5	Implicit
Grok 4.1	Implicit
Gemini 3.0 Pro Preview	Implicit

2.2.2 Overthinking in AI Models

3 Methods

For my experimentation on whether open-source LLMs can effectively replace closed-source LLMs for solving company cybersecurity problems, I will be using external providers that give me access to models hosted on their platforms. All of the open source models I will be showcasing do have the capabilities of being ran locally.

The downside to running models locally is the limit of available compute power to the common individual. For example, my computer hardware specs are:

- **CPU**: AMD Ryzen 9 9950X 16-Core Processor
- **RAM**: 4 sticks of 32 GB DDR6 RAM running at 3600 MT/s
- **GPU**: NVIDIA GeForce RTX 3090 (24 GB VRAM)

To show the limits of compute, I will go through trying to run one of these models locally on my own computer. The model I will attempt to run is GLM 4.5-air.

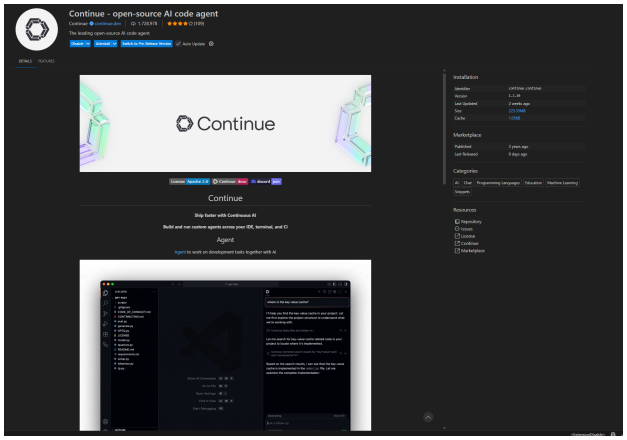
3.1 Using External Providers

3.1.1 Openrouter

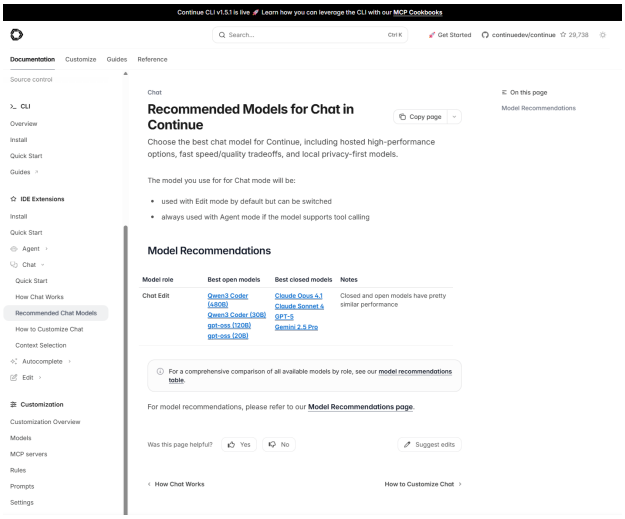
3.1.2 Continue.dev

Continue.dev is an open source VSCode extension and also offers a CLI to allow AI to interact with your filesystem. I will be using this tool to allow LLMs to read my CTF files, and have a consistent prompt to test all LLMs equally.

Continue.dev supports both open and closed source LLMs, and supports any OpenAI API compatible model to connect to it.



(a) Continue.dev VSCode Extension



(b) Continue.dev Supported Models

Figure 5: Continue.dev features

3.2 SmileyCTF 2025 – SaaS (Cryptography) *(Difficulty: Easy)*

3.2.1 Solution

The server selects primes p, q with

$$p \equiv q \equiv 3 \pmod 4, \qquad n = pq, \qquad e = 65537.$$

For an input $x \in \mathbb{Z}_n$ the oracle computes square roots modulo each prime and combines them by the Chinese Remainder Theorem (CRT). Concretely, let

$$r_p \equiv x^{(p+1)/4} \pmod p, \qquad r_q \equiv x^{(q+1)/4} \pmod q,$$

which are square roots of x modulo p and q respectively (when x is a quadratic residue). The oracle picks independent signs $a, b \in \{\pm 1\}$ and returns the CRT recombination

$$r = a\, r_p \cdot A + b\, r_q \cdot B \pmod n,$$

where we define the CRT basis elements

$$A \equiv q \cdot (q^{-1} \bmod p), \qquad B \equiv p \cdot (p^{-1} \bmod q),$$

so that

$$A \equiv 1 \pmod p, \quad A \equiv 0 \pmod q, \qquad B \equiv 0 \pmod p, \quad B \equiv 1 \pmod q.$$

Thus the oracle's output is one of the four values

$$R = \left\{ a\, r_p A + b\, r_q B \pmod n \;:\; a, b \in \{\pm 1\} \right\}.$$

Square roots modulo n and factor recovery

Let p and q be distinct primes with $p \equiv q \equiv 3 \pmod 4$, and let $n = pq$. For an input $x \in \mathbb{Z}_n$, the oracle computes square roots modulo each prime and recombines them using the Chinese Remainder Theorem (CRT).

Square roots modulo a prime

Let p be an odd prime with $p \equiv 3 \pmod 4$. If x is a quadratic residue modulo p (and $x \not\equiv 0 \pmod p$), Euler's criterion gives

$$x^{\frac{p-1}{2}} \equiv 1 \pmod p.$$

Consider

$$\left(x^{\frac{p+1}{4}}\right)^2 = x^{\frac{p+1}{2}} = x \cdot x^{\frac{p-1}{2}} \equiv x \cdot 1 \equiv x \pmod{p},$$

so $x^{\frac{p+1}{4}}$ is indeed a square root of x modulo p:

$$\boxed{\left(x^{\frac{p+1}{4}}\right)^2 \equiv x \pmod{p}}.$$

If x is not a quadratic residue modulo p, the same computation yields

$$\left(x^{\frac{p+1}{4}}\right)^2 \equiv -x \pmod{p},$$

Thus in all non-degenerate cases the value r_p produced by the local exponentiation satisfies

$$r_p^2 \equiv \pm x \pmod{p},$$

and similarly $r_q^2 \equiv \pm x \pmod{q}$.

CRT recombination of square roots modulo n

Let

$$r_p \equiv x^{\frac{p+1}{4}} \pmod{p}, \qquad r_q \equiv x^{\frac{q+1}{4}} \pmod{q},$$

and define the CRT basis elements

$$A \equiv q \cdot (q^{-1} \bmod p), \qquad B \equiv p \cdot (p^{-1} \bmod q),$$

so that

$$A \equiv 1 \pmod{p},\ A \equiv 0 \pmod{q}, \quad B \equiv 0 \pmod{p},\ B \equiv 1 \pmod{q}.$$

For independent signs $a, b \in \{\pm 1\}$, the four CRT recombinations are

$$r_{a,b} \equiv a r_p A + b r_q B \pmod{n}.$$

Recovering n from complementary roots

If two roots correspond to opposite signs, say (a, b) and $(-a, -b)$, then

$$r_{a,b} + r_{-a,-b} \equiv 0 \pmod{n}.$$

Taking integer representatives in $[0, n-1]$, this means

$$r_{-a,-b} \equiv n - r_{a,b}.$$

Hence, after sorting the four integer roots, the sum of the smallest and largest root recovers n:

$$\boxed{n = r_{\min} + r_{\max}}.$$

Extracting a prime via a GCD

Different sign choices produce distinct roots. Consider a pair differing only in the q-component:

$$r_{a,b} = a r_p A + b r_q B, \qquad r_{a,-b} = a r_p A - b r_q B.$$

Their difference is

$$r_{a,b} - r_{a,-b} = 2b\, r_q B.$$

Reducing this difference modulo the primes gives the two congruences

$$r_{a,b} - r_{a,-b} \equiv 0 \pmod{p}, \qquad r_{a,b} - r_{a,-b} \equiv 2b\, r_q \pmod{q}.$$

Thus the difference is divisible by p and congruent to $2br_q$ modulo q. Therefore the greatest common divisor yields the prime factor:

$$\boxed{\gcd(r_{a,b} - r_{a,-b},\, n) = p.}$$

Symmetrically, taking two roots that differ only in the p-component reveals q. In practice one collects the four CRT roots, picks an appropriate pair, and computes

$$p = \gcd(r_i - r_j,\, n), \qquad q = n/p.$$

Forge the signature

Once p, q are known we compute

$$\varphi(n) = (p-1)(q-1), \qquad d \equiv e^{-1} \pmod{\varphi(n)}.$$

Given the challenge's printed value m the RSA signature is forged as

$$\boxed{s \equiv m^d \pmod{n}.}$$

Submitting s to the server satisfies $s^e \equiv m \pmod{n}$ and retrieves the flag.

3.2.2 Summary of steps used in the exploit

1. Repeatedly query the oracle with a fixed number (this number does **NOT** have to be a quadratic residue. It can be a number that does not have a square root. the solver uses $x = 3$) to collect several of the modular roots.
2. From the four roots compute n as the sum of the smallest and largest root.
3. Use a difference of an appropriate pair and $\gcd(\cdot, n)$ to recover one prime p (the other is $q = n/p$).
4. Compute $d = e^{-1} \pmod{\varphi(n)}$ and then $s = m^d \bmod n$.

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