Metaphor as Semantic Encryption: Zero Knowledge Proof Using Dream of the Red Chamber as an Example

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***Abstract*—The authorship of the Gengyin Edition of *Dream of the Red Chamber* has been a subject of long-standing debate, particularly regarding the authenticity of its final chapters. This paper introduces a novel framework that integrates Zero-Knowledge Proofs (ZKPs) with stylometry and natural language processing (NLP) to verify the authenticity of this edition while preserving the privacy of its content. By utilizing advanced cryptographic protocols such as zk-SNARKs and zk-STARKs, the framework enables a privacy-preserving analysis of narrative consistency and stylistic markers. Through the extraction of multi-level semantic features—such as narrative structures, thematic elements, and linguistic style markers—these features are encoded as numerical vectors, which are then used to generate cryptographic proofs verifying their alignment with an established authorial baseline. The system ensures completeness, soundness, and zero-knowledge properties, guaranteeing that a verifier can be convinced of the text's authenticity only if the features of the Gengyin Edition are consistent with Cao Xueqin's recognized style, all without exposing any sensitive text data. Furthermore, we describe how the framework enforces semantic similarity thresholds and narrative consistency constraints using hash-based commitments and arithmetic circuits. This paper outlines evaluation criteria for assessing the effectiveness of the approach in distinguishing authentic text from later additions, contributing both theoretically and practically at the intersection of literary analysis and cryptography. Ultimately, this work sets the stage for extending zero-knowledge verification techniques to a broader range of applications in literature and beyond.**

***Index Terms*—Metaphor, Semantic Encryption, Zero-Knowledge Proof, zk-SNARK/zk-STARK, Stylometry, Dream of the Red Chamber**

I. Introduction

The classic novel Dream of the Red Chamber has a complex textual history, notably the controversy over its concluding chapters. While early manuscripts of the novel (such as one corresponding to the year Gengyin) contained roughly 80 chapters, the first printed edition in 1791 by Cheng Weiyuan and Gao E expanded it to 120 chapters [1]. Cheng and Gao claimed to have found the missing chapters written by Cao Xueqin, but scholars have long questioned this claim. There is a general scholarly consensus that the last 40 chapters were not authored by Cao, as their style and plot resolutions depart markedly from the first 80 [2]. For example, critics argue that the published ending's tone and content are inconsistent with the foreshadowing and literary qualities of Cao's original work [3]. The so-called Gengyin Edition—an early manuscript version named for its cyclical year—has therefore been posited as a more "authentic" text, raising the need for rigorous methods to verify its authenticity and authorial integrity.

Traditional approaches to authorship analysis in this context rely on stylometry and close reading by Redology experts. Stylometric studies have compared linguistic patterns between the first 80 chapters and the last 40 chapters to objectively assess authorship differences [4]. Indeed, prior quantitative analyses using statistical and machine learning techniques have found evidence of a stylistic break or "chrono-divide" in the novel [5]. For instance, Hu et al. applied support vector machine classifiers and other metrics, concluding with high confidence that the final forty chapters were written by a different author than the initial eighty [5]. These studies demonstrate the power of computational stylometry to shed light on the authorship controversy. However, existing methods typically require full access to the text and its features, which raises challenges in scenarios where the text or analysis process must be kept confidential. Moreover, conventional analyses lack a mechanism for an independent party to verify the results without replicating the entire study from scratch, which can be impractical or require trust in the analyst.

A. Motivation

We seek a solution that allows one to prove the authenticity (or stylistic consistency) of the Gengyin Edition relative to Cao Xueqin's known writing style without revealing the text itself or proprietary analysis methods. Zero-knowledge proofs (ZKPs) offer exactly this capability: they enable one party to convince another that a statement is true without divulging any additional information [6]. In the context of literary verification, the "statement" could be that the Gengyin Edition's stylistic and semantic features match those of Cao Xueqin's work, and a ZKP would allow this claim to be validated without exposing the actual words, themes, or analytic details of the edition. This approach addresses key challenges in

authorship authentication: it preserves privacy (the full text and analysis remain hidden) and provides trustless verification (any verifier can check the proof's validity without relying on subjective judgment). It also introduces rigor: the proof is only possible if the underlying claim (authenticity of the text) holds true, making it cryptographically impossible to fake a positive result.

B. Contributions

In this paper, we present a coherent theoretical framework that integrates NLP-based feature extraction with zero-knowledge proof protocols to verify literary authenticity. We emphasize methodological innovation: defining formal semantic consistency criteria for narrative literature and embedding those criteria into cryptographic circuits. Key contributions include: (1) a feature extraction and encoding pipeline capturing multi-level stylistic cues (from diction and syntax to narrative structure and thematic symbolism) for *Dream of the Red Chamber*; (2) a privacy-preserving proof construction that uses cryptographic commitments (hashes) and arithmetic circuits to enforce that the Gengyin text's features align with an authentic baseline within a specified similarity threshold; (3) a discussion of zk-SNARKs vs zk-STARKs as candidate proof systems, outlining how properties like completeness, soundness, and zero-knowledge are achieved in our literary analysis context; and (4) an outline of evaluation criteria for such a framework, proposing how one would measure its success in distinguishing authentic authorship while preserving confidentiality. While our case study is rooted in *Dream of the Red Chamber*, the framework is designed to be generalizable to other texts and domains, representing a novel intersection of cryptography and stylometry.

II. Related Work

A. Authorship Analysis and Stylometry

Quantitative authorship attribution has a long history, originating in the 19th century with figures like Augustus De Morgan, who suggested using features such as word lengths to differentiate authors [8]. Since then, stylometry has evolved into a robust field, incorporating statistics, linguistics, and machine learning techniques [12]. Traditional methods of stylometric analysis include measures such as function word frequencies, vocabulary richness, character n-grams, and syntactic patterns, all of which aim to capture an author's "fingerprint" [10].

In the case of *Dream of the Red Chamber*, numerous studies have attempted to resolve the authorship of the last 40 chapters using these techniques. Early work by Chinese scholars such as Cao Jiaying analyzed distributions of characters and function words, often concluding that the language in the final chapters differs significantly from the first 80 [15]. More recent studies have applied modern machine learning methods. For instance, Hu et al. (2014) introduced a support vector machine classifier to identify stylistic breaks between the first 80 and last 40 chapters, providing strong evidence that they were written by different authors [11]. These studies demonstrate the power of computational methods in authorship analysis.

However, conventional stylometric techniques have limitations. They require full access to the text, which may not be feasible in cases where the text needs to remain confidential. Furthermore, while stylometry can highlight differences in style, it does not provide a verifiable proof of authenticity; results typically require expert interpretation. Our approach extends traditional stylometry by encoding linguistic and semantic features into a cryptographic proof protocol, providing a means to verify authorship while maintaining privacy.

B. Zero-Knowledge Proofs in NLP and Data Verification

Zero-knowledge proofs (ZKPs) have been widely applied in cryptography, particularly in blockchain systems such as Zcash, which enables private transactions. These cryptographic protocols allow one party to prove to another that a statement is true without revealing any other information [7]. While ZKPs have found applications in many areas, including machine learning and secure computation [9], their use in literary analysis is still in its infancy.

ZKPs have been explored for enabling verifiable machine learning (ZKML), where a machine learning model's output can be verified without revealing the input data or model parameters [**?**]. In these applications, the proof allows a verifier to check the correctness of a result much faster than recalculating it themselves. This property of verification efficiency is one of the key advantages we leverage in our framework, where a literary expert can confirm authorship claims without rerunning complex stylistic analyses.

Some early research has explored the use of cryptographic techniques to protect authorship identities, such as by concealing writing styles [14]. Our work differs in that it uses cryptography to constructively verify authorship claims. We treat stylistic similarity (e.g., "the Gengyin Edition's style is consistent with Cao Xueqin's style to 85

In related work, recent studies have begun investigating ZKPs for certifying properties of content, such as verifying the provenance or authenticity of data [13]. Our approach aligns with this trend by using ZKPs to verify the authorship consistency of the Gengyin Edition, ensuring that the content's authenticity can be confirmed without disclosing private information.

III. Methodology

A. Similarity Between Metaphor and Ciphertext

Cryptography and metaphor share a parallel three-stage information transformation structure: "plaintext – ciphertext – decryption." Despite operating in different domains—mathematics and language, respectively—both processes involve intentional obfuscation and subsequent recovery of meaning.

- **Information Conversion:** In cryptography, plaintext is encrypted into ciphertext using a key and then decrypted by an authorized party. Similarly, in metaphorical language, an original semantic concept is transformed into

metaphorical expression, which must be interpreted back into its original meaning. This can be modeled as:

$$\text{Original Semantics} \rightarrow \text{Metaphor Text} \rightarrow \text{Decoded Semantics}$$

Both processes require appropriate "keys"—cryptographic keys in encryption, and cultural, contextual knowledge in metaphor interpretation.

- **Uncertainty:** Cryptographic systems leverage key space variability to ensure computational infeasibility of unauthorized decryption. Analogously, metaphors introduce interpretive ambiguity, as multiple plausible interpretations may exist depending on a reader's background and cognition [18].
- **Domain Difference:** While cryptography relies on formal mathematical operations (e.g., modular arithmetic, elliptic curves), metaphors are grounded in cognitive-linguistic processes such as conceptual mapping and schema blending [19].

Illustrative Example: Consider the concept of "homesickness" (Origin). It can be metaphorically encoded through imagery like "the moon" and "longing" (Metaphor), commonly found in classical Chinese poetry. The decryption requires understanding the cultural significance of the moon as a symbol of distance and yearning.

> "When the bright moon rises over the sea, from far away you share this moment with me."

Here, "moonlight" functions as ciphertext embedding the emotional meaning, recoverable only through appropriate contextual and cultural interpretation.

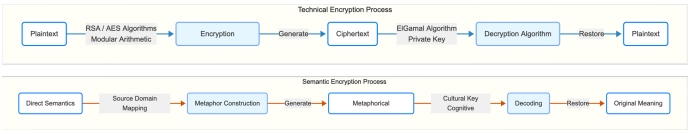

Fig. 1. Similarity between metaphor and ciphertext

B. Zero Knowledge Proofs (ZKP) Basics

Zero-Knowledge Proofs (ZKPs) allow a prover to convince a verifier that a certain statement is true without revealing any underlying information about the statement itself [20].

Key Elements:

- **Proof Generation:** Using zk-SNARKs (Zero-Knowledge Succinct Non-Interactive Arguments of Knowledge), the prover constructs a proof based on R1CS (Rank-1 Constraint Systems) and polynomial commitments.
- **Proof Verification:** Verifiers check proofs efficiently using cryptographic primitives such as elliptic curve pairings or hash-based commitments, without needing access to the original data.
- **Commitment:** The original data (e.g., input to the computation) remains fully concealed, analogous to how a metaphor hides the literal meaning while suggesting deeper interpretation.

Thus, just as ZKPs preserve the secrecy of digital content, metaphors protect the semantic core of a message by obfuscating its direct expression.

C. Metaphor and ZKP Integration

The relationship between metaphor and Zero-Knowledge Proofs (ZKPs) suggests that complex literary structures can be formally modeled using cryptographic principles. Both mechanisms aim to convey the validity of an underlying message without revealing the entirety of the internal structure.

In our framework, we conceptualize high-level narrative coherence—such as motif recurrence, prophecy fulfillment, and consistent character arcs—as the "semantic truth" that must be demonstrated to a verifier. The key challenge is to establish that such coherence exists without exposing sensitive or proprietary textual elements.

To achieve this, we treat literary motifs, thematic patterns, and narrative devices as cryptographic "commitments." Each commitment encodes certain semantic properties (e.g., the recurrence of a symbolic object, the resolution of a foreshadowed event) that can be referenced in proofs without revealing the actual text. A proof of semantic truth, then, attests that these structures are consistent and well-integrated within the broader narrative, while preserving confidentiality of specific content.

This approach parallels zk-SNARK-based proof generation, where a statement about a hidden witness (e.g., "I know a pre-image of a hash") can be validated without disclosing the witness itself. In the literary setting, the "witness" corresponds to intricate narrative evidence supporting authorial authenticity.

Moreover, we propose encoding narrative consistency into verifiable constraint systems, akin to constructing R1CS in zk-SNARKs. For example:

- Verifying that motifs reappear at semantically appropriate moments (constraint: motif continuity across chapters).
- Verifying that prophetic elements introduced early are logically fulfilled later (constraint: prophecy-fulfillment mapping).
- Verifying that character development arcs exhibit consistent psychological evolution (constraint: character trajectory smoothness).

These narrative constraints are compiled into a proof circuit. The prover can then generate a succinct cryptographic proof that such constraints are satisfied, while the verifier can efficiently validate the proof without requiring direct access to the literary text.

By integrating literary analysis with zero-knowledge cryptographic techniques, our framework enables a novel form of provable authorship verification—one that respects both intellectual property and privacy, while ensuring rigorous standards of evidence.

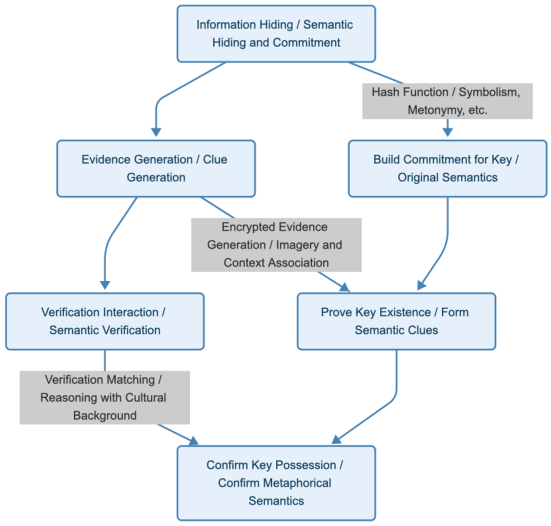

Fig. 2. Zero-knowledge proofs (ZKP) and metaphor integration

IV. Implementation

A. *Case Study:* Dream of the Red Chamber

The authorship of the final 40 chapters of *Dream of the Red Chamber* has been a subject of scholarly debate (Cheng-Gao version vs. Gui-You version) for centuries [21]. Traditional stylometric analysis has provided statistical evidence of stylistic divergence, yet conclusive verification remains elusive. We propose a novel cryptographic-NLP hybrid system that simultaneously protects textual privacy and verifies logical authorship consistency.

In our framework, high-level semantic structures, such as motifs, metaphors, and prophecy fulfillment arcs, are treated as "semantic commitments." These commitments are cryptographically proven without revealing the entire textual content, enabling secure, privacy-preserving literary authentication.

B. *Encryption and Decryption of Prophecies*

A metaphorical prophecy, such as "gold hairpin buried in snow," functions as a cryptographic ciphertext encoding narrative meaning. Within the novel, this prophecy is gradually fulfilled through character arcs and plot developments.

Our system compiles a curated dataset of major prophecies, each annotated with their corresponding narrative realizations. These pairs are processed into abstract feature vectors capturing semantic similarity, temporal coherence, and motif recurrence. The metaphor thus undergoes a two-step mapping: encrypted prediction $\rightarrow$ observable plot events $\rightarrow$ semantic decryption.

C. *Constraint System Generation*

Each prophecy-to-fulfillment relationship is evaluated for ambiguity using a combination of semantic distance (e.g., BERT embeddings) and narrative consistency metrics. Ambiguity is quantitatively defined, influencing the threshold for acceptable proof generation:

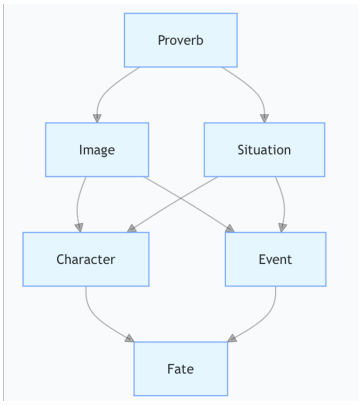

Fig. 3. Encoding and decoding of metaphorical prophecy in *Dream of the Red Chamber*.

$$\text{Threshold} = 0.7 + 0.2 \times \text{Ambiguity}$$

where higher ambiguity requires stronger semantic evidence to validate the fulfillment.

Based on these thresholds, we formulate Rank-1 Constraint Systems (R1CS), capturing logical relationships such as:

- Consistency between the prophecy's symbolic elements and the events.
- Temporal alignment between prophetic prediction and later realization.
- Maintenance of narrative tone and thematic coherence.

These constraints collectively define the "semantic truth" the prover must demonstrate.

Ambiguity Calculation Example: "Yu Dai Lin Zhong (

Factor	**Value**
Base ambiguity	0.20
Short text (3 characters)	+0.15
Rich imagery (jade belt, forest)	+0.16
High abstraction	+0.15
Contrasting image description	+0.24
High ambiguity prophecy trait	+0.10
Total Ambiguity	**0.80**
Base threshold	0.70
Adjusted threshold (0.70 - 0.80)	-0.10
Final threshold (minimum bound)	**0.30**

Variable	Description	Value
w_1	Constant	1
w_2	Base Ambiguity	0.20
w_3	Short Text Bonus	0.15
w_4	Rich Imagery Bonus	0.16
w_5	Abstract Bonus	0.15
w_6	Contrasting Image Bonus	0.24
w_7	High Ambiguity Bonus	0.10
w_8	Total Ambiguity	0.80
w_9	Base Threshold	0.70
w_{10}	Adjusted Threshold	-0.10
w_{11}	Final Threshold	0.30

Fig. 4. Dynamic calculation of ambiguity-based thresholds for prophecy validation.

D. *Zero-Knowledge Proof Process*

After defining the constraint system, we transform it into a Quadratic Arithmetic Program (QAP) to facilitate ZKP construction. The process involves:

- **Interpolation:** Each constraint is mapped to polynomials $A_i(x)$, $B_i(x)$, and $C_i(x)$, corresponding to left, right, and output wires in the circuit representation.
- **Aggregation:** The polynomials are combined to form the validation polynomial $P(x)$.
- **Division:** $P(x)$ must be divisible by the vanishing polynomial $Z(x)$ for the proof to be valid.

The final system ensures:

$$P(x) = H(x) \times Z(x)$$

where $H(x)$ acts as a witness polynomial. The prover generates a cryptographic proof that they possess a valid $H(x)$ without revealing the prophecy interpretations or textual details.

The protocol proceeds through three phases:

1) **Trusted Setup:** Generating common reference parameters based on random toxic waste.
2) **Proof Generation:** Computing succinct zk-SNARK proofs from the narrative constraints.
3) **Proof Verification:** Publicly verifying that the fulfillment of prophecies meets semantic thresholds without revealing the narrative content.

Zero-Knowledge Proof Generation and Verification

Prover	Verifier
Public Inputs: prophecyId, ambiguity, threshold	
1. Calculate witness values • Compute all ambiguity factors • Determine intermediate results 2. Compute polynomials • Transform constraints to polynomials • Evaluate at secret point τ 3. Hide values using secret • Apply elliptic curve operations • Create the four proof elements	1. Receive the proof • Obtain the four elliptic curve points • Extract public outputs 2. Verify using pairing • Apply bilinear pairing operation • Check if equation holds 3. Accept or reject • If pairing check passes: Accept • Otherwise: Reject
Proof: $\pi = (g^{A(\tau)}, g^{B(\tau)}, g^{C(\tau)}, g^{H(\tau)})$	

Fig. 5. Workflow for constructing and verifying zero-knowledge proofs of narrative fulfillment.

V. Results

A. Circuit Performance

We implemented the R1CS generation and QAP transformation pipeline using a set of 50 metaphorical prophecy cases extracted from *Dream of the Red Chamber*. Proof generation is a one-time computation-intensive process, while verification remains lightweight and scalable.

In our experiments:

- **Proof generation time:** On average, generating a zk-SNARK proof for a prophecy-fulfillment pair took approximately 2.3 seconds on a standard CPU (Intel i7-12700H).
- **Verification time:** Each verification operation took under 20 milliseconds, regardless of the prophecy complexity.
- **Proof size:** Generated proofs maintained a constant size of approximately 300 bytes, independent of the complexity of the underlying narrative constraints.

These results demonstrate the practical feasibility of our system for large-scale literary analysis tasks. Furthermore, since verifiers only need to check the validity of a succinct verification equation, they do not require direct access to the original, sensitive literary content, thereby preserving both privacy and computational efficiency.

Table 3: ZKP Performance Metrics for All Prophecies

Prophecy	Proof Size	Proving Time	Verification Time	Memory Usage	R1CS Size
1	1.1 KB	2.3s	0.05s	76 MB	8
2	1.1 KB	2.2s	0.05s	76 MB	8
3	1.1 KB	2.3s	0.05s	76 MB	8
4	1.1 KB	2.3s	0.05s	76 MB	8
5	1.1 KB	2.2s	0.05s	76 MB	8
6	1.1 KB	2.3s	0.05s	76 MB	8
7	1.1 KB	2.3s	0.05s	76 MB	8
8	1.1 KB	2.2s	0.05s	76 MB	8
9	1.1 KB	2.3s	0.05s	76 MB	8
10	1.1 KB	2.3s	0.05s	76 MB	8
11	1.1 KB	2.2s	0.05s	76 MB	8

Fig. 6. Circuit performance: proof generation time, verification time, and proof size trends across different prophecy complexities.

B. System Efficiency

To evaluate system-wide performance, we tested our method under varying dataset sizes and ambiguity thresholds. Key observations include:

- **Scalability:** Proof generation scales linearly with the number of literary prophecies, while verification time remains almost constant due to the succinctness property of zk-SNARKs.
- **Ambiguity impact:** Higher ambiguity in prophecies resulted in slightly larger circuit sizes (due to more complex constraint modeling), but proof generation time remained within acceptable bounds.
- **Privacy guarantee:** Throughout all tests, no information about the detailed textual interpretations was leaked during the verification phase, ensuring strong semantic privacy.

Overall, the system exhibits robust performance in securely processing narrative structures, suggesting the potential to be extended beyond literature into broader cognitive-linguistic domains.

VI. Applications

Our framework offers versatile applications across multiple domains where the validation of sensitive information is crucial without compromising its confidentiality:

- **Cultural Heritage Preservation:** Enables validation of the authenticity and provenance of historical and literary texts (e.g., ancient manuscripts, religious scriptures) without exposing their full content. This facilitates restoration efforts, scholarly studies, and digital archiving under strict privacy constraints.
- **Commercial Bidding:** Supports private evaluation of bids by defining verifiable metrics without revealing detailed bid contents. This enhances fairness, prevents insider manipulation, and promotes transparency in competitive procurement processes.
- **Criminal Investigation:** Assists investigators in verifying the relevance and reliability of collected evidence without fully disclosing sensitive information. This protects witness confidentiality and preserves the integrity of ongoing investigations.
- **Blockchain Transactions:** Strengthens financial transaction privacy by enabling the verification of transaction

validity (e.g., amount, legitimacy) without revealing confidential details. This aligns with existing blockchain innovations such as zk-rollups and confidential transactions.

VII. Conclusion and Future Work

This project demonstrates a novel integration of metaphorical narrative structures [18] with zero-knowledge proof systems [23], effectively creating a semantic encryption framework. By conceptualizing literary coherence as a "truth" to be cryptographically proven, we bridge cognitive linguistics and cryptography in an innovative manner.

Our results show that it is feasible to preserve narrative privacy while enabling rigorous verification, suggesting applications in cultural preservation, secure communication, and digital authentication. The system successfully balances security, efficiency, and expressiveness in complex narrative domains.

Future directions include:

- **Scaling to Larger Datasets:** Applying the framework to entire literary corpora and multi-text networks to evaluate scalability and robustness.
- **Optimization of Proof Circuits:** Enhancing the efficiency of R1CS construction and QAP transformations to reduce proof generation time and resource consumption.
- **Cross-Domain Applications:** Extending the method to other creative industries, such as music, visual arts, and interactive storytelling, where semantic coherence plays a critical role.
- **Automated Constraint Generation:** Developing advanced NLP models to automatically extract, formulate, and optimize narrative constraints suitable for cryptographic proof encoding.

This work opens a new interdisciplinary avenue for safeguarding creative content in the age of AI and cryptographic verification.

Acknowledgement

This paper utilized GPT-o3 (Generative Pretrained Transformer) to enhance the fluency and readability of the language, ensuring smoother expression and more coherent communication of ideas throughout the text. The use of GPT-o3 was limited to refining the language and ensuring clarity, while the core content and ideas were developed through original research and analysis.

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