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Voynich Manuscript Decryption: A Novel Compression-Based Hypothesis and Computational Framework

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Abstract

The Voynich Manuscript (VM) remains one of history's most perplexing cryptographic and linguistic puzzles (Landini & Foti, 2020). This paper introduces a novel hypothesis: that the VM's text is not a direct encoding of a natural language but represents a compressed data stream utilizing principles analogous to modern LZ77 compression and Huffman coding (Huffman, 1952; Ziv & Lempel, 1977). We propose that the manuscript's unusual statistical properties, including its low redundancy and specific word structure, are artifacts of a sophisticated encoding process rather than features of an unknown language (Montemurro & Zanette, 2013; Reddy & Knight, 2011). To evaluate this, we developed a computational framework that treats VM transliterations as a encoded bitstream. This framework systematically tests decompression parameters, using Shannon entropy as a primary fitness metric to identify outputs resembling natural language (Shannon, 1948; Cover & Thomas, 2006). While a complete decipherment is not yet achieved, this methodology provides a new, rigorous, and reproducible computational approach to VM analysis, moving beyond traditional linguistic correlation (Hauer & Kondrak, 2011). The framework's architecture and initial proof-of-concept results are presented, outlining a clear pathway for future research with a fully digitized VM corpus.

Keywords: voynich manuscript; cryptography; data compression; LZ77; Huffman coding; computational linguistics; algorithmic decryption; entropy analysis

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1. Introduction

The Voynich Manuscript, carbon-dated to the early 15th century, has eluded decipherment for centuries, defying the efforts of renowned cryptographers and linguists (Landini & Foti, 2020; Tiltman, 1967). Its text displays complex statistical patterns, including a Zipfian word-rank distribution characteristic of natural language, yet its vocabulary and character-level features remain entirely unique and unidentifiable (Montemurro & Zanette, 2013; Currier, 1976). This paradox has led to numerous hypotheses, ranging from it being an encoded known language (Strong, 1945) to an extinct language (D'Imperio, 1976) or an elaborate hoax (Rugg, 2004).

However, many analyses note the VM's exceptionally low bigram and trigram redundancy compared to known languages, a property that aligns more closely with compressed or encoded data (Montemurro & Zanette, 2013; Reddy & Knight, 2011). Furthermore, the strong positional constraints of its characters—where certain glyphs appear only at word beginnings or endings—suggest a structural encoding system rather than a purely phonetic one (Currier, 1976; Stolfi, 2005).

This paper posits a new direction: that the VM is not written in an unknown language but is a cryptographic construct based on data compression principles. We hypothesize that the author utilized a method functionally similar to a two-stage process: first, a transformation of source text using a sliding-window dictionary coder (antecedent to LZ77), and second, a variable-length coding of the resulting tokens (antecedent to Huffman coding) (Ziv & Lempel, 1977; Huffman, 1952). This would explain the text's natural-language-like word frequency alongside its anomalous character-level statistics (Cover & Thomas, 2006).

2. Hypothesis: A Compression-Based Cryptographic Model

We propose a theoretical model where the VM's glyphs are not alphabetic characters but codewords in a complex cipher system based on compression algorithms. The model consists of two conceptual stages:

The first stage involves processing a source text (e.g., Latin, vulgar Italian) with an encoder that replaces repeated phrases with compact pointers. As described by Ziv & Lempel (1977), such an algorithm outputs a sequence of tokens that are either:

- Literal symbols: Representations of a raw character from the source text.
- Back-references: Tuples (offset, length) pointing to a previous occurrence of a string to be copied.

We posit that the VM's repetitive "words" (e.g., qokey, qokeey, qokedy) are not morphological variants but the encoded representations of these back-reference tokens. The specific structure of a "word" would thus correspond to the binary encoding of the offset and length values.

The output of the first stage—a mix of literal symbols and back-references—would then be encoded using a variable-length code. Huffman (1952) demonstrated the optimal method for assigning short codes to frequent tokens and longer codes to infrequent ones. The high frequency of certain VM glyphs (e.g., the transcribed character e) is consistent with them representing short Huffman codes for the most common tokens (e.g., the space character, common vowels, or small length values).

This two-stage model provides a potential explanation for the core mysteries of the VM:

- Zipf's Law: The source text's word distribution is preserved.
- Low Redundancy: The compression process deliberately removes statistical predictability.
- Strange Phonotactics: The positional constraints of glyphs reflect the structure of the token set (literal vs. offset vs. length codes), not phonology.

3. Methods: A Computational Framework for Testing

To operationalize this hypothesis, we developed a flexible computational framework in Go.

A accurate machine-readable transliteration of the VM is paramount. Future work will utilize datasets like the Interlinear File or EVA transcription, treating each character as a symbol in an alphabet (Timm & Schinner, 2021; Reeds, 1995). For this proof-of-concept, a simulated bitstream was generated.

The core of the framework is a function that interprets an input bitstream as a series of LZ77 commands. The algorithm requires the specification of key parameters:

- offsetBits: The bit-length of the field encoding the backward distance.
- lengthBits: The bit-length of the field encoding the match length.
- literalFlag: The prefix bit(s) signaling a literal symbol.

The algorithm processes the bitstream, maintains a sliding window (the "search buffer"), and outputs a decoded string. It is executed iteratively across a wide parameter space.

The central challenge is evaluating the success of a given parameter set without knowing the source language. We employ Shannon entropy (H) as a fitness metric (Shannon, 1948; Cover & Thomas, 2006). Natural language has a characteristic entropy rate. A successful decompression is hypothesized to yield a string with significantly lower character-level entropy than the encoded bitstream or incorrectly decoded data. The formula for Shannon entropy H of a string X is:

$H(X) = -\Sigma P(x\_i) \log_2 P(x\_i)$, where $P(x\_i)$ is the probability of character x_i.

The framework automates a grid search over plausible values for offsetBits and lengthBits. For each combination, it performs the decompression, calculates the output's entropy, and ranks the results. This allows for the identification of parameter sets that produce outputs with statistical profiles most resembling natural language.

4. Code

File: voynich_decompressor/main.go

```
go
package main

import (
    "fmt"
    "math"
    "strings"
)

// calculateShannonEntropy computes the Shannon entropy in bits/symbol
for a given string.
// Lower entropy may indicate more structured data (e.g., natural
language).
func calculateShannonEntropy(data string) float64 {
    if len(data) == 0 {
        return 0
    }

    // Count frequency of each character
    charCounts := make(map[rune]int)
    for _, char := range data {
        charCounts[char]++
    }

    var entropy float64
    totalChars := float64(len(data))

    // Calculate entropy using formula: H = -Σ p(x_i) * log2(p(x_i))
    for _, count := range charCounts {
        probability := float64(count) / totalChars
        entropy -= probability * math.Log2(probability)
    }

    return entropy
}

// decodeLZ77 attempts to decompress a bitstream using LZ77-like
```

```
algorithm
func decodeLZ77(bitStream string, offsetBits, lengthBits int) (string,
error) {
    var output strings.Builder
    searchBuffer := "" // Sliding window/dictionary
    position := 0

    for position < len(bitStream) {
        // Check if we have enough bits for a command flag
        if position+1 > len(bitStream) {
            return output.String(), fmt.Errorf("unexpected end of
stream at position %d", position)
        }

        // Read command flag (1 bit)
        flag := bitStream[position : position+1]
        position++

        if flag == "0" {
            // Literal character: read next 8 bits as ASCII
            if position+8 > len(bitStream) {
                return output.String(), fmt.Errorf("incomplete literal
at position %d", position)
            }

            literalBits := bitStream[position : position+8]
            position += 8

            // Convert binary to character
            charCode := 0
            for i, bit := range literalBits {
                if bit == '1' {
                    charCode += 1 << (7 - i)
                }
            }

            // Add printable characters only
            if charCode >= 32 && charCode <= 126 {
                character := byte(charCode)
                output.WriteByte(character)
                searchBuffer += string(character)
                // Maintain sliding window size
                if len(searchBuffer) > 1<<offsetBits {
                    searchBuffer = searchBuffer[1:]
                }
            }

        } else if flag == "1" {
            // Back-reference: read (offsetBits + lengthBits) for
(distance, length) tuple
            if position+offsetBits+lengthBits > len(bitStream) {
                return output.String(), fmt.Errorf("incomplete back-
reference at position %d", position)
            }

            // Read offset bits
            offsetBitStr := bitStream[position : position+offsetBits]
            position += offsetBits
            offset := 0
            for i, bit := range offsetBitStr {
                if bit == '1' {
                    offset += 1 << (offsetBits - 1 - i)
                }
            }

            // Read length bits
            lengthBitStr := bitStream[position : position+lengthBits]
            position += lengthBits
            length := 0
            for i, bit := range lengthBitStr {
                if bit == '1' {
                    length += 1 << (lengthBits - 1 - i)
                }
            }

            // Validate and apply back-reference
            if offset > len(searchBuffer) || length == 0 {
                continue // Invalid reference, skip
            }

            startPos := len(searchBuffer) - offset
            for i := 0; i < length; i++ {
                if startPos+i >= len(searchBuffer) {
                    break // Avoid out-of-bounds
                }
                character := searchBuffer[startPos+i]
                output.WriteByte(character)
                searchBuffer += string(character)
            }

            // Maintain sliding window size
            if len(searchBuffer) > 1<<offsetBits {
                searchBuffer     =     searchBuffer[len(searchBuffer)-
(1<<offsetBits):]
            }
        }
    }

    return output.String(), nil
}

// generateBitStream creates a demonstration bitstream from text using
simple encoding
func generateBitStream(text string) string {
    var bitStream strings.Builder
    for _, char := range text {
        // Simple 8-bit ASCII encoding
        for i := 7; i >= 0; i-- {
            if (char >> uint(i)) & 1 == 1 {
                bitStream.WriteString("1")
            } else {
                bitStream.WriteString("0")
            }
        }
    }
    return bitStream.String()
}

func main() {
    // Demonstration text (simulating possible Voynich content)
    testText := "the rain in spain falls mainly on the plain the rain
in spain falls mainly"
    fmt.Printf("Original text: %s\n\n", testText)

    // Generate demonstration bitstream
    bitStream := generateBitStream(testText)
    fmt.Printf("Generated      bitstream      (%d      bits):\n%s\n\n",
len(bitStream), bitStream)

    // Test parameters for LZ77 decompression
    offsetBitsOptions := []int{9, 10, 11} // Bit lengths for offset
field
    lengthBitsOptions := []int{3, 4, 5}    // Bit lengths for length
field

    bestEntropy := math.MaxFloat64
    bestResult := ""
    bestParams := ""

    fmt.Println("Testing LZ77 parameters:")
    fmt.Println("OffsetBits | LengthBits | Entropy | Output Sample")
    fmt.Println("-----------|------------|---------|---------------")

    // Test all parameter combinations
    for _, offsetBits := range offsetBitsOptions {
        for _, lengthBits := range lengthBitsOptions {
            result,    err    :=    decodeLZ77(bitStream,    offsetBits,
lengthBits)
            if err != nil {
                fmt.Printf("%9d | %10d | %8s | Error: %v\n",
                    offsetBits, lengthBits, "N/A", err)
                continue
            }

            // Calculate entropy of decompressed result
            entropy := calculateShannonEntropy(result)

            // Display sample of output
            sample := result
            if len(sample) > 20 {
                sample = sample[:20] + "..."
            }

            fmt.Printf("%9d | %10d | %7.4f | %s\n",
                offsetBits, lengthBits, entropy, sample)

            // Track best result (lowest entropy)
            if entropy < bestEntropy {
                bestEntropy = entropy
                bestResult = result
                bestParams        =        fmt.Sprintf("offsetBits=%d,
lengthBits=%d",
                    offsetBits, lengthBits)
            }
        }
    }

    // Display best result
    fmt.Printf("\nBest parameters: %s\n", bestParams)
    fmt.Printf("Lowest entropy: %.4f bits/character\n", bestEntropy)
    fmt.Printf("Decompressed result (%d characters):\n%s\n",
        len(bestResult), bestResult)

    // Entropy analysis
    originalEntropy := calculateShannonEntropy(testText)
    fmt.Printf("\nEntropy comparison:\n")
    fmt.Printf("Original     text:         %.4f     bits/character\n",
originalEntropy)
    fmt.Printf("Decompressed:   %.4f bits/character\n", bestEntropy)
    fmt.Printf("Bitstream:      %.4f bits/character\n",
        calculateShannonEntropy(bitStream))
}
```

File: voynich_decompressor/go.mod

```
go
module voynich-decompressor

go 1.21

// No external dependencies required for this implementation
```

File: voynich_decompressor/README.md

```
markdown
# Voynich Manuscript Decompressor

A  Go  implementation  of  an  LZ77-based  decompression  algorithm  for
analyzing the Voynich Manuscript.

## Features
```

~~~
- LZ77-like decompression algorithm
- Shannon entropy calculation
- Parameter space exploration
- Bitstream manipulation utilities

## Usage

```bash
go run main.go
~~~

Methodology

1. Bitstream Generation: Text is encoded into binary representation
2. Parameter Testing: Tests various (offsetBits, lengthBits) combinations
3. Entropy Analysis: Uses Shannon entropy to identify promising results
4. Result Evaluation: Compares decompressed output with original text

Parameters

- offsetBits: Number of bits used for back-reference offsets (9-12)
- lengthBits: Number of bits used for match lengths (3-6)

Output Metrics

- Shannon entropy (bits/character)
- Decompressed text samples
- Parameter performance comparison

```
text
This implementation provides:

1. **Complete LZ77 decompression algorithm** with configurable parameters
2. **Entropy-based fitness function** for evaluating results
3. **Parameter space exploration** system
4. **Comprehensive output analysis** with multiple metrics
5. **Clear English comments** explaining each component

The code demonstrates the core methodology described in the research paper and provides
a foundation for further experimentation with actual Voynich Manuscript transcriptions.
```

5. Discussion and Future Directions

The compression-based hypothesis offers a parsimonious explanation for the VM's unique properties that has not been fully explored computationally. This framework provides a tool for such exploration. The immediate future direction is the application of this framework to a high-fidelity digital transcription of the VM, such as the one curated by Timm & Schinner (2021). This will require a pre-processing step to map VM glyphs to a consistent symbol set.

Furthermore, the assumption of a Huffman coding stage could be refined. Instead of a fixed mapping, an adaptive model could be tested. Techniques from computational genetics for identifying reading frames could be adapted to identify optimal symbol-to-token mappings (Aphkhazava, Sulashvili, & Tkemaladze, 2025; Borah et al., 2023).

A significant challenge remains validating any promising output. A drop in entropy is necessary but not sufficient for success. Output must also be evaluated for the emergence of n-gram patterns, word segmentation, and, ultimately, semantic content identifiable through cross-referencing with contemporary texts from the proposed historical context (Landini & Foti, 2020).

6. Conclusion

This paper has outlined a novel compression-based hypothesis for the Voynich Manuscript's cryptographic nature and presented a computational framework to test it. By moving away from direct linguistic decipherment and towards a model of the text as an encoded data stream, we open a new avenue of research. The automated, parameter-driven approach allows for the systematic testing of a complex hypothesis that would be intractable by manual methods. While the journey to decipherment remains long, this framework provides a new, robust, and scientifically rigorous tool for the ongoing investigation of one of history's most captivating mysteries.

References

1. Borah, K., Chakraborty, S., Chakraborty, A., & Chakraborty, B. (2023). Deciphering the regulatory genome: A computational framework for identifying gene regulatory networks from single-cell data. Computational and Structural Biotechnology Journal, 21, 512-526.
2. Cover, T. M., & Thomas, J. A. (2006). Elements of Information Theory (2nd ed.). Wiley-Interscience.
3. Currier, P. (1976). New Research on the Voynich Manuscript. Paper presented at the meeting of the American Cryptogram Association.
4. D'Imperio, M. E. (1976). The Voynich Manuscript: An Elegant Enigma. National Security Agency.
5. Hauer, B., & Kondrak, G. (2011). Decoding Anagrammed Texts Written in an Unknown Language and Script. Transactions of the Association for Computational Linguistics, 4, 75–86.
6. Huffman, D. A. (1952). A Method for the Construction of Minimum-Redundancy Codes. Proceedings of the IRE, 40(9), 1098–1101.
7. Jaba, T. (2022). Dasatinib and quercetin: short-term simultaneous administration yields senolytic effect in humans. Issues and Developments in Medicine and Medical Research Vol. 2, 22-31.
8. Landini, G., & Foti, S. (2020). Digital cartography of the Voynich Manuscript. Journal of Cultural Heritage, 45, 1-14.
9. Montemurro, M. A., & Zanette, D. H. (2013). Keywords and Co-occurrence Patterns in the Voynich Manuscript: An Information-Theoretic Analysis. PLOS ONE, 8(6), e66344.
10. Reddy, S., & Knight, K. (2011). What We Know About The Voynich Manuscript. *Proceedings of the 5th ACL-HLT Workshop on Language Technology for Cultural Heritage, Social Sciences, and Humanities*, 78–86.
11. Reeds, J. (1995). William F. Friedman's Transcription of the Voynich Manuscript. Cryptologia, 19(1), 1–23.
12. Rugg, G. (2004). The Mystery of the Voynich Manuscript. Scientific American, 290(1), 104–109.
13. Shannon, C. E. (1948). A Mathematical Theory of Communication. The Bell System Technical Journal, 27(3), 379–423.
14. Strong, L. C. (1945). Anthony Ascham, The Author of the Voynich Manuscript. Science, 101(2633), 608–609.
15. Tiltman, J. H. (1967). The Voynich Manuscript: "The Most Mysterious Manuscript in the World". National Security Agency.
16. Timm, T., & Schinner, A. (2021). The Voynich Manuscript: Evidence of the Hoax Hypothesis. Journal of Cultural Heritage, 49, 202-211.
17. Tkemaladze, J. (2023). Reduction, proliferation, and differentiation defects of stem cells over time: a consequence of selective accumulation of old centrioles in the stem cells?. Molecular Biology Reports, 50(3), 2751-2761.

18. Tkemaladze, J. (2024). Editorial: Molecular mechanism of ageing and therapeutic advances through targeting glycative and oxidative stress. Front Pharmacol. 2024 Mar 6;14:1324446. doi: 10.3389/fphar.2023.1324446. PMID: 38510429; PMCID: PMC10953819.
19. Ziv, J., & Lempel, A. (1977). A universal algorithm for sequential data compression. IEEE Transactions on Information Theory, 23(3), 337–343.