

INFORMATION MODELS FOR PREDICTION

PROJECT 1 - ALGORITHMIC THEORY OF INFORMATION COURSE

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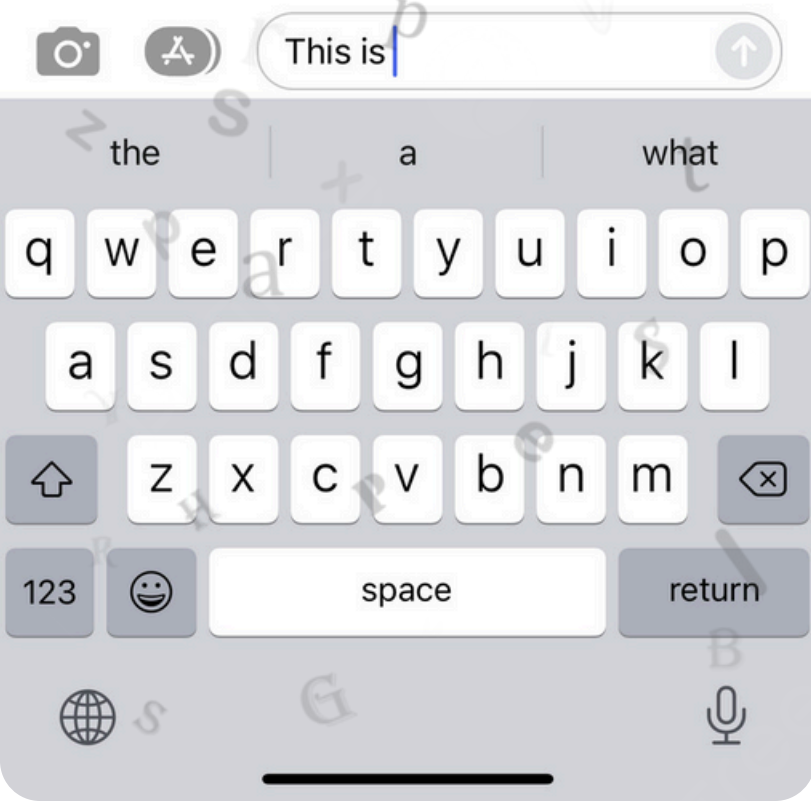
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Introduction

- Implemented Finite-Context Models (FCMs) for text analysis and predictive text generation.
- **Aim:** Estimate symbol distributions in text for statistical analysis and predictive text generation.
- Developed two main C++ programs:
 - **fcm** (statistical analysis)
 - **generator** (text generation)
- Evaluated models performance with varying parameters (context order k , smoothing α).
- Implemented and compared JSON/binary model export formats.



Key Programs Developed

fcf:

Reads input text, constructs FCF by updating frequency tables, computes probabilities with Laplace smoothing, calculates Average Information Count.

generator:

Generates new text based on a trained model using weighted random selection and can also do all operations **fcf** does.

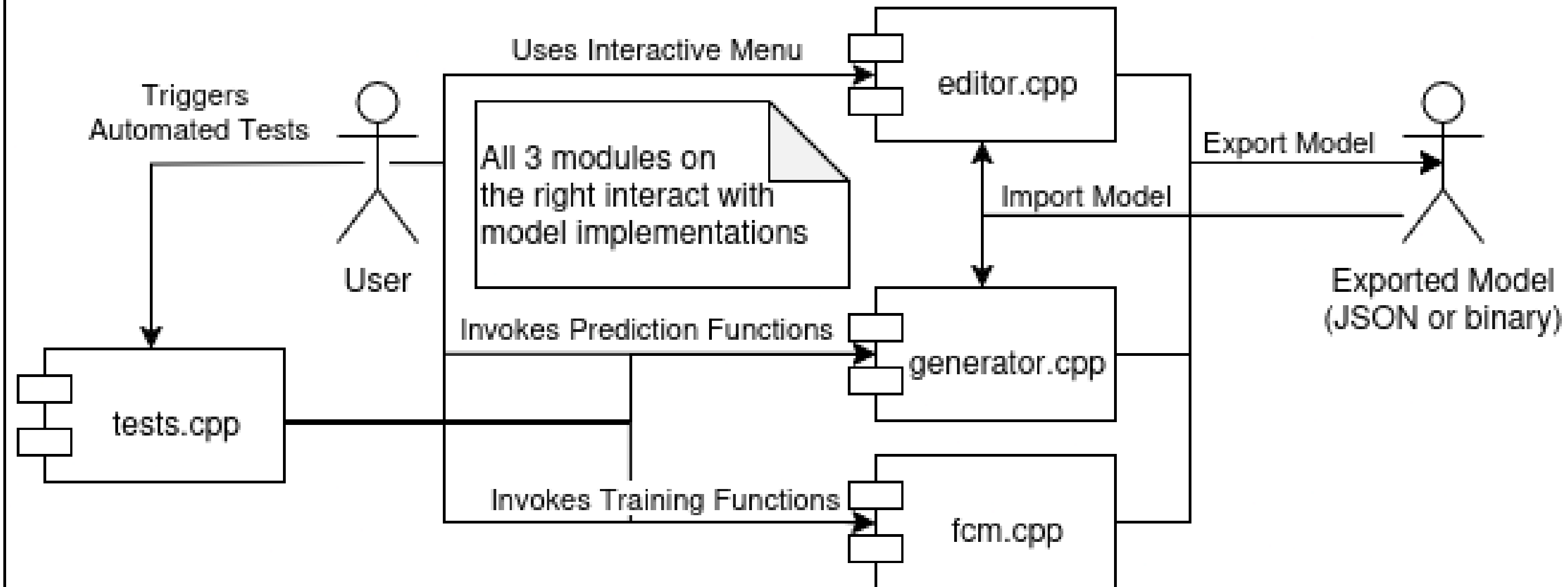
editor:

User-friendly interactive text-based interface for model manipulation.

tests:

Automated testing, with multiple combination of parameters, for models validation.

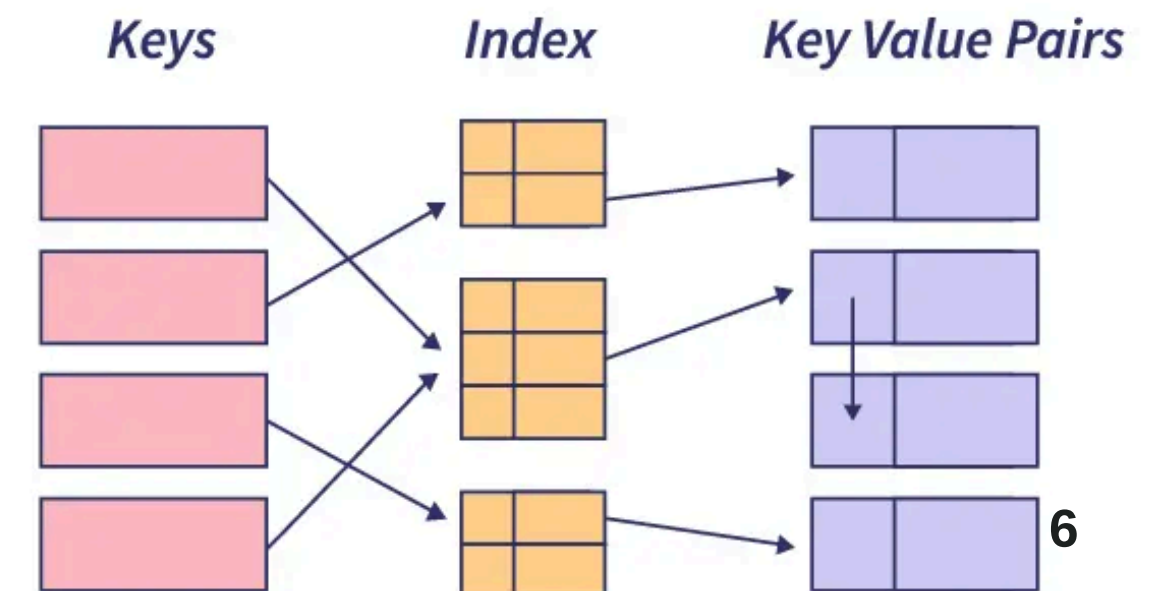
Workflow Diagram



Model Implementation

Data Structures

- **Hash Tables** (*unordered_map*) for efficient $O(1)$ lookups.
- **Frequency Table**: counts occurrences of symbols after contexts.
- **Context Count Table**: tracks context occurrences.
- **Probability Table**: stores computed probabilities.
- **Alphabet Set**: stores unique symbols.



Implementation Steps

Learning Phase

- UTF-8 character splitting.
- Sliding window processing.
- Dynamic alphabet update.
- Context frequency updating.
- Probability computation with Laplace smoothing.

Average Information Content Calculation

- Quantifies the model quality (lower == better)
- Measured in bits per symbol (bps)

Text Generation

- Context-based sampling.
- Weighted random selection via cumulative distribution.
- Rolling context updates.

Standard FCM vs Recursive FCM



Standard FCM

Uses fixed context length k

Recursive FCM

Incorporates multiple context lengths (k down to 1).

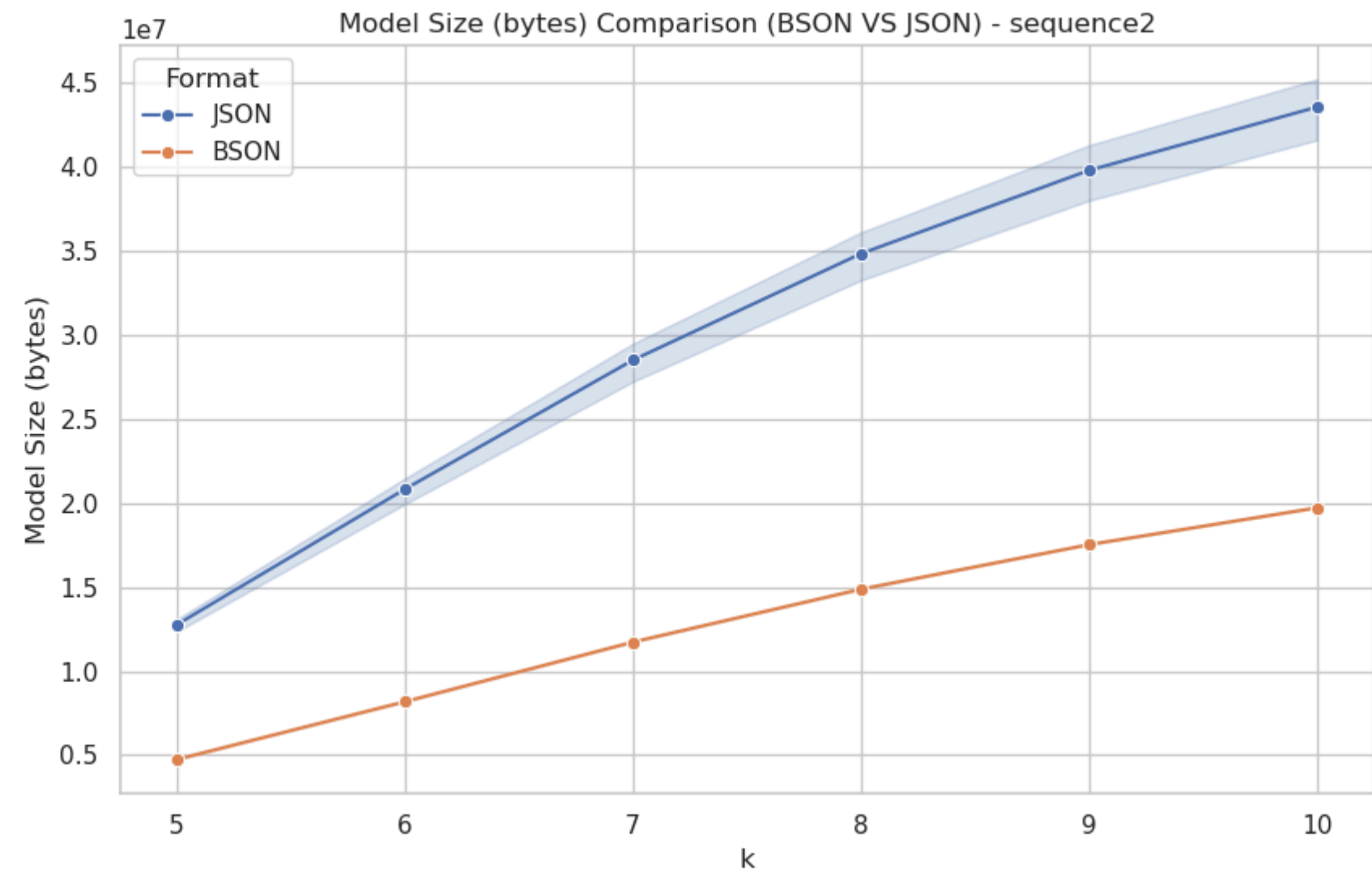
RFCM features:

- Recursive learning for all context lengths.
- Separate frequency tables for each context length.
- Recursive probability retrieval with fallback mechanism.

Model Export/Import

Formats

- **JSON:**
 - Human-readable.
 - Larger file size.
- **Binary (BSON):**
 - Compact & Efficient.
 - Non-human readable.



Editor and Auxiliary Features

- Interactive menu for model creation and manipulation.
- Models properties display.
- Continuous refinement.
- Syntactic analysis via word list comparison.

```
=====
FCM MODEL EDITOR
=====
No model loaded.
1. Create New Model
2. Import Model
0. Exit
=====
Enter your choice: 1
```

```
=====
FCM MODEL EDITOR
=====
Current Model: New Model
===== FCM MODEL SUMMARY =====
Order (k): 3
Smoothing (alpha): 0.1
Model is unlocked
Alphabet size: 0 unique symbols
Contexts: 0 unique contexts
Total transitions: 0
=====
1. Create New Model
2. Import Model
=====
---- CORE MODEL OPERATIONS ----
3. Learn From Text
4. Predict Next Symbols
5. Compute Information Content
=====
---- MODEL MANIPULATION ----
6. Lock/Unlock Model
7. Rename Model
8. Clear Model
9. Export Model
=====
0. Exit
=====
Enter your choice: 3
```

Generated Text Samples

- Example outputs with different parameters.
- Syntactic validation evaluation (in this example, ~75% of the words were recognized).

```
Enter the context to predict from: porta
Enter the number of symbols to predict: 200
Starting prediction with context: 'porta'
Context has 5 characters, model k=5
Using rolling context: 'porta'
Prediction:
o mar aparece toda Frandecerá desbarata
Inda não cego enganosas se parece que esse a tanto menos de Anfitriete deleito,
Pelo neto de tão dirá que tenro a espanto
Que tão fizerem ao mesta, por que tant
```

```
=====
Do you want to perform a syntactic analysis? (y/n): y
Enter the filename to load the word list from: syntactic_analysis/ptWords.txt
Read 13929038 characters from syntactic_analysis/ptWords.txt
Syntactic Analysis Results:
Total words in prediction: 37
Valid words in prediction: 28
Percentage of valid words: 75.6757%
```

Experimental Results

Effect of Context Size

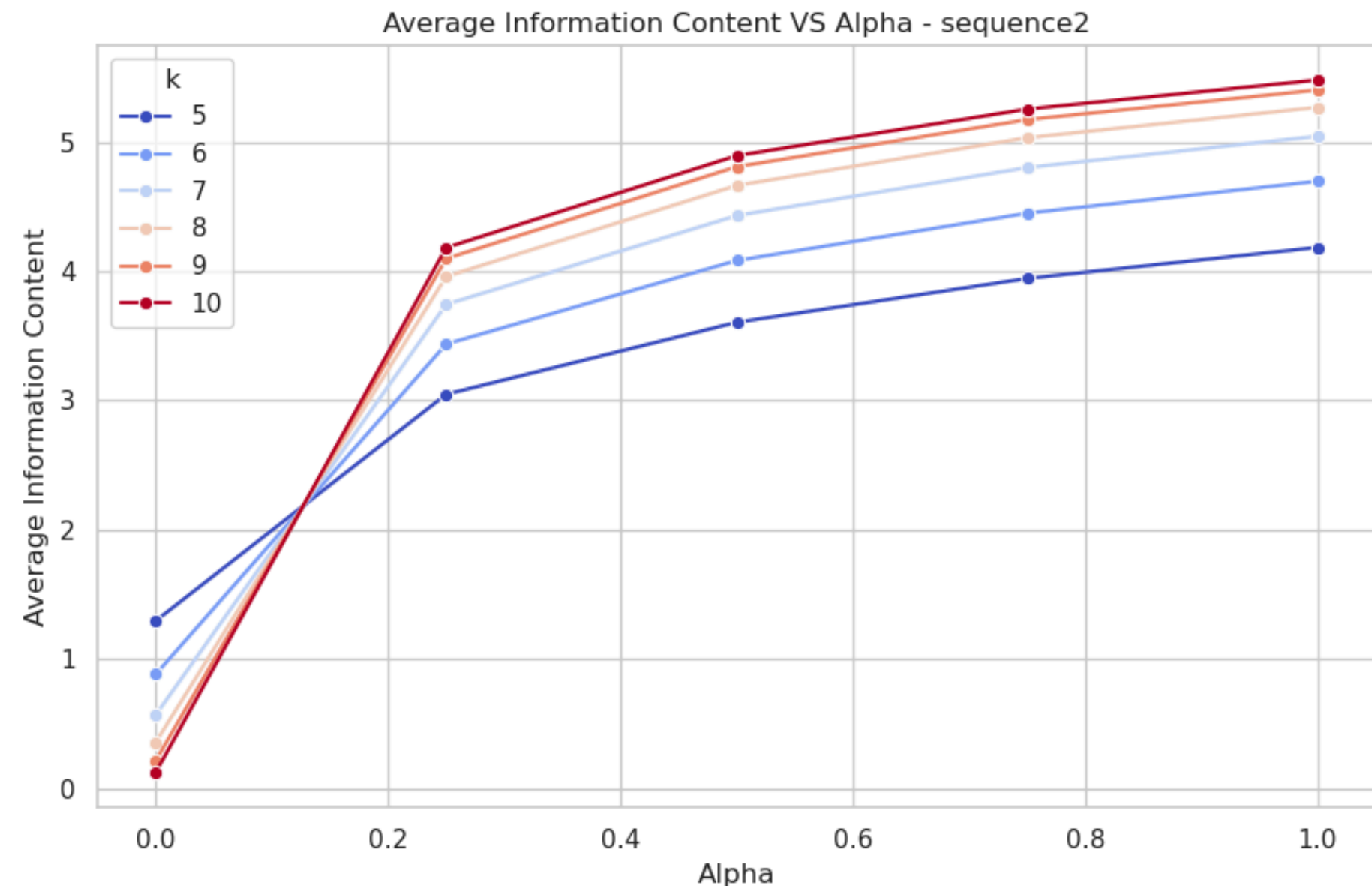
Context Size k	Average Information Content (bits per symbol)
1	3.34668
3	2.4112
5	2.41512
10	3.14763
30	3.24091

Average Information Content, based on k – sequence2.txt

Experimental Results

Impact of Smoothing Parameter

- Moderate *alpha* values generally produce more reliable models.
- Need to balance over-smoothing and under-smoothing.

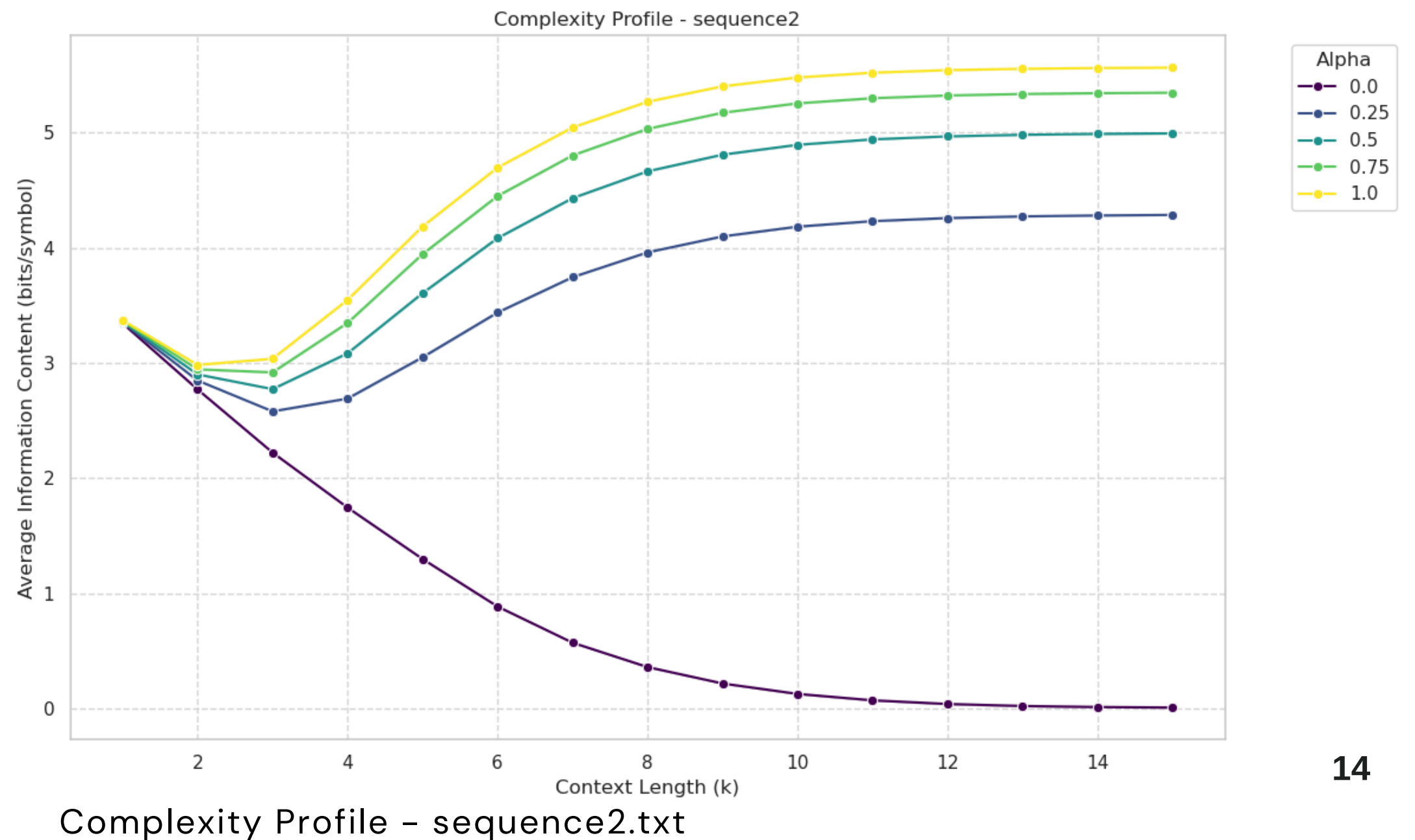


Average Information Content, based on alpha - sequence2.txt

Experimental Results

Complexity Profiles

- Lower-order contexts contribute significantly to prediction accuracy.
- Sharp decreases at low α values indicate highly structured sequences.
- Higher α values show more randomness and long-range dependencies



Main Findings

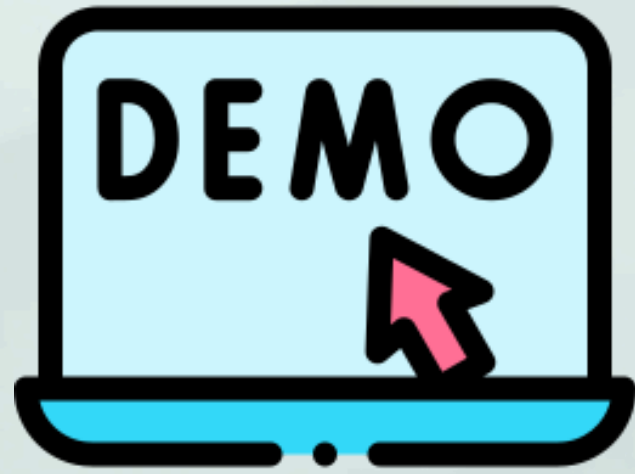
- Optimal context size (k) between 3–5 for tested datasets.
- Moderate smoothing parameters (~ 0.1) produce more reliable models.
- Binary serialization reduced storage by 40–60% compared to JSON.
- Generated text exhibited recognizable stylistic elements.
- Syntactic analysis showed moderate–high rate of valid words.



Future Work

- Adaptive context selection based on pattern availability.
- Enhanced dictionary integration for linguistic coherence.
- Interactive text generation with real-time suggestions.
- Improved dictionary-based correction mechanisms.





LIVE DEMO

+

QUESTIONS

