

# Statistical Properties of Compression Analytics (CA)

Kurtis Shuler\*, Alexander Foss\*, Travis Bauer+, Richard Field‡, Christina Ting+

\*Department of Statistical Sciences, 05573, +Computational Decision Science, 05554, ‡Data Science & Applications 05553

## Project Goals:

- Improve CA through better understanding of its underlying statistical properties
- Advance CA through development of “non-local” compression techniques that can identify and utilize nonadjacent structure present within a byte stream for better ML performance

## Applications:

- Text analysis, detection of disinformation campaigns, DNA/RNA sequence analysis, cybersecurity

## What is Compression Analytics?

- **CA uses compression to achieve machine learning tasks:** Anomaly detection, classification, clustering, etc.
- File compression algorithms used to measure similarity or shared information across items

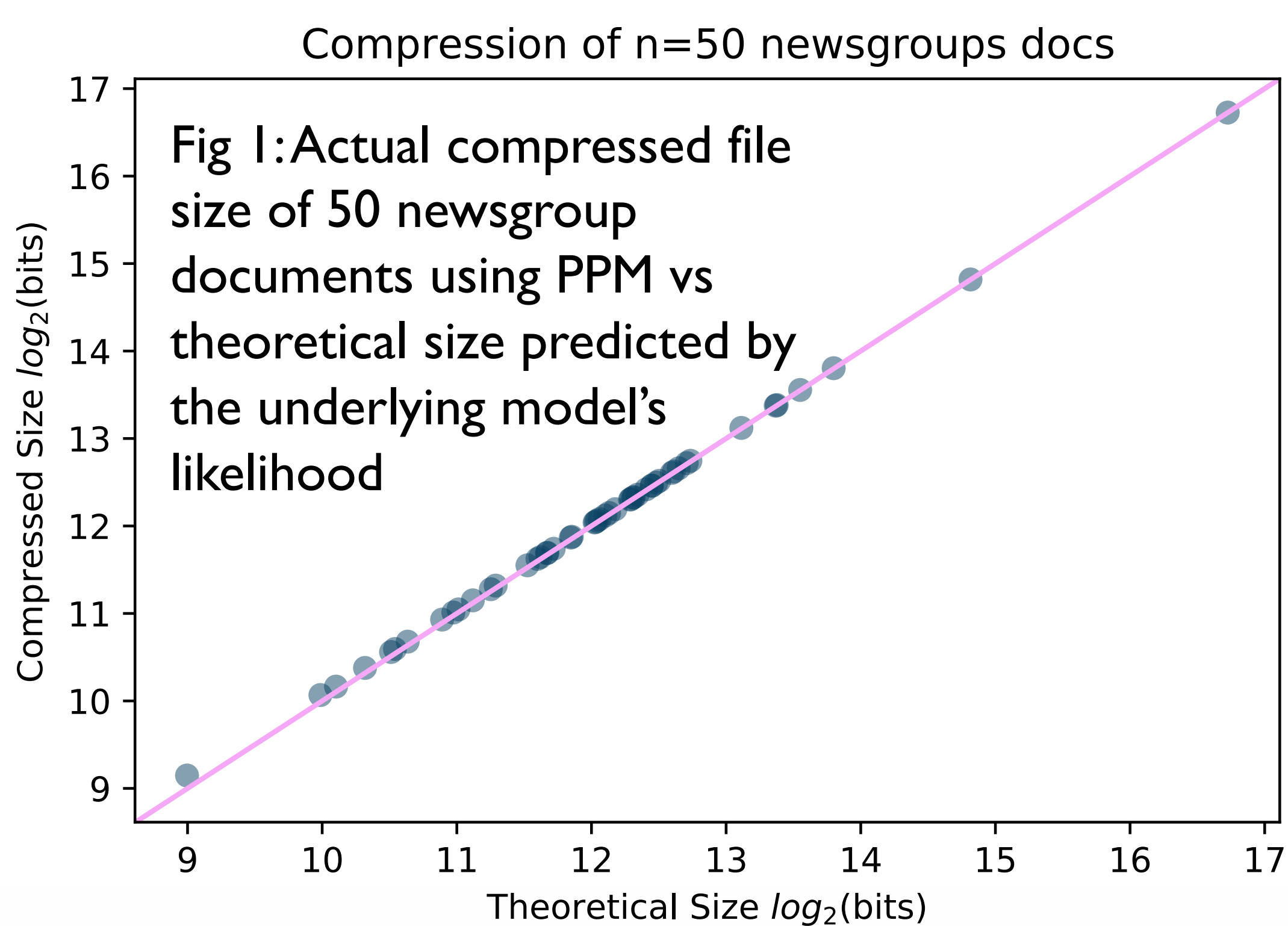
## Advantages of CA

- **CA is “featureless” in the sense that it can be applied to any byte stream**
- Allows rapid model development and prototyping with **minimal analyst intervention, even on unstructured data**
- Many open source and COTS compression tools readily available

## CA for Classification

- Consider a classification problem with  $M$  different classes
- The goal is to assign class label  $m \in \{1, \dots, M\}$  to a new, unlabeled byte stream
- For each class a different compression model will be produced (“trained”) using the labeled training data
- For the new byte stream, assign a class label based on which of the  $M$  compression models compresses it best

## CA and Model Likelihood



- Entropy encoders use statistical models to compress files by encoding more frequently occurring symbols with a smaller number of bits
- A lower bound for the number of bits required to encode a stream is related to the stream's entropy, and is given by Shannon's source coding theorem
- We show for this class of compression algorithms the **classification rule is equivalent to choosing  $m$  to be the class corresponding to the compression/statistical model with the highest likelihood**

## Proposed Method: Model Selection

- KL divergence gives the expected number of extra bits required to encode a stream when the true (typically unknown) byte stream distribution is  $f(x)$ , but is encoded using  $g(x|\theta)$

$$I(f, g) = \sum_x f(x) \log_2 \left( \frac{f(x)}{g(x|\theta)} \right)$$

- Akaike Information Criterion (AIC) provides an approximately unbiased estimator of expected relative KL information
- **For entropy encoders, model selection criteria can be used to select an optimal compression algorithm**
- Figures 2 and 3 demonstrate this using 100 training documents and 100 test documents from the 20 newsgroups dataset

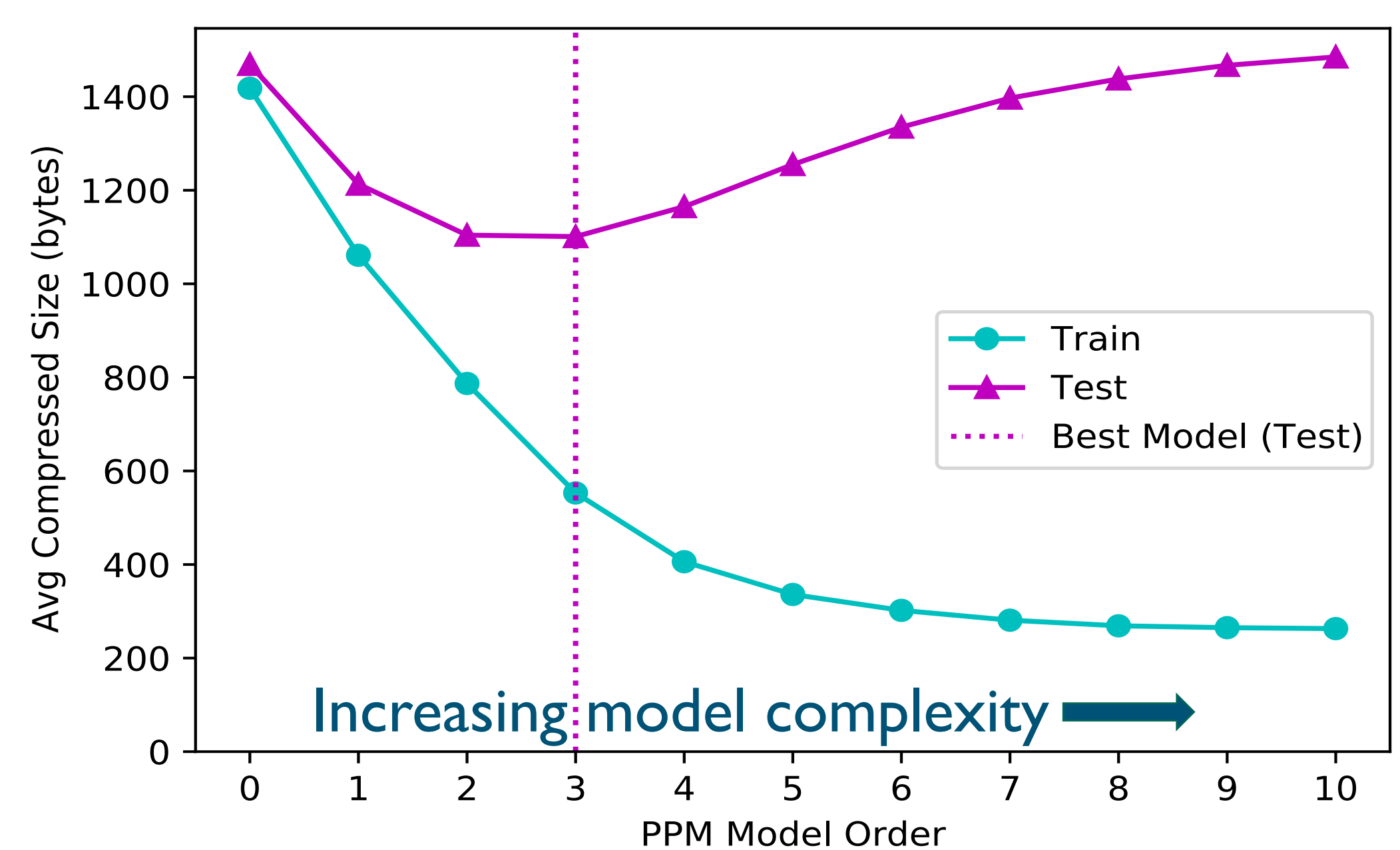


Fig 2: Bias/variance tradeoff in file compression size

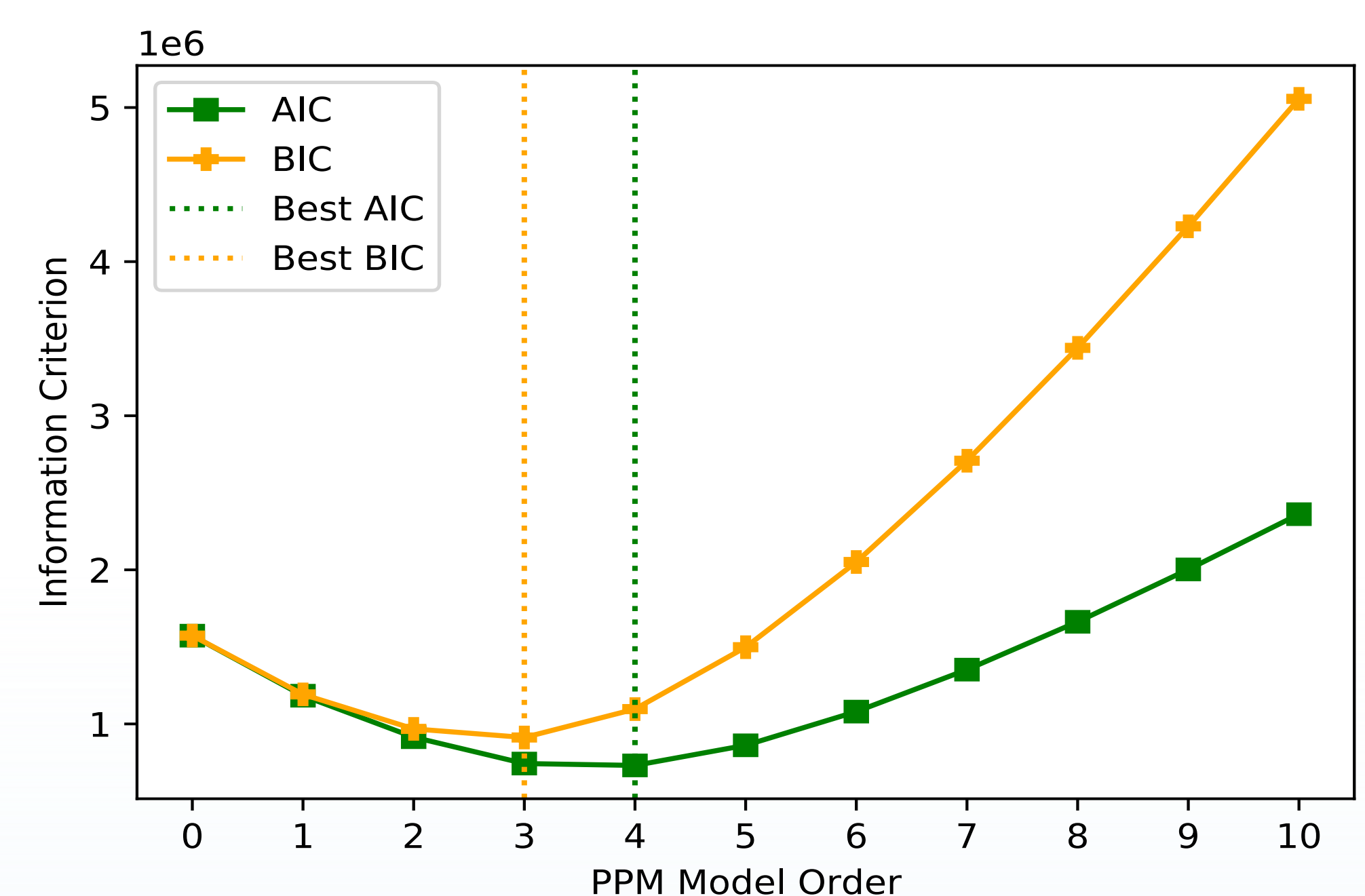


Fig 3: Model selection criterion for different PPM models

Statistical interpretation of CA yielded novel model selection technique with promising initial results on real-world data