Predictive Coding For Lossless Dataset Compression

Unordered source coding in theory and practice

Traditional Source Coding

Consider a sequence (X_1, X_2, \ldots, X_n) with $X_1, X_2, \ldots, X_n \stackrel{iid}{\sim} P_X$

Given a random variable over an alphabet \mathcal{X} , a **lossless source code (l.s.c.)** consists of functions $f : \mathcal{X} \to \{0, 1\}^*$ and $g : \{0, 1\}^* \to \mathcal{X}$ such that g(f(x)) = x

To encode symbols with few bits, we usually minimize the average code word length:

 $M^*(P_X) \triangleq \min \{ \mathbb{E} \left[l(f(X)) \right] \mid (f,g) \text{ is a prefix-free l.s.c.} \}$

Motivation

Many large datasets in research, archives, ML training, etc.

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Traditional compression algorithms operate on stream data. If we don't need to preserve order on elements, we can save space and bandwidth with a "dataset" compression algorithm.

Dataset Source Coding

Consider a "dataset", i.e. a set of samples where order doesn't matter: $\{X_1, X_2, \ldots, X_n\}$

Define a **lossless dataset source code (l.d.s.c)** $f: \mathcal{X}^n \to \{0, 1\}^*$ and $g: \{0, 1\}^* \to \mathcal{X}^n$ such that $g(f(x^n)) = \pi \circ x^n$ for all $x^n \in \mathcal{X}^n$ where π is a permutation.

For a l.d.s.c. we minimize $M_n^*(P_X) \triangleq \min \left\{ \mathbb{E}\left[l(f(X^n)) \right] \mid (f,g) \text{ is a prefix-free l.d.s.c.} \right\}.$

Note: dataset code length \leq sequence code length

Theoretical Results

Theorem 1 (I.d.s.c. via data structures):

Let $\widetilde{X}^n = \pi \circ X^n$, where π is a permutation drawn uniformly at random. Moreover, let S be such that 1) $S \to X^n \to \widetilde{X}^n$ and $X^n \to S \to \widetilde{X}^n$ 2) $H(S|X^n) = H(S|\widetilde{X}^n) = 0$ Then $M^*(P_S) = M_n^*(P_X)$,

$$\begin{split} H(S) &\leq M_n^*(P_X) < H(S) + 1 \\ \text{and} \ H(S) &= I(X^n; \widetilde{X}^n) \leq \min\{|\mathcal{X}| \log_2(n+1), n \log_2 |\mathcal{X}|\} \end{split}$$

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Experiments

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Idea: in many data, the "features" are not truly independent from each other. For example, pixels in an image.

Predictive coding: instead of encoding every value, can encode some values, a model to obtain adjacent ones, and the "error" between predictions and true value.

Combining ideas from **Theorem 1** and JPEG-LS:

- 1. Build nearest neighbors graph of dataset
- 2. Obtain reordering by traversing a MST
- 3. Train predictor on context from *within* images and *adjacent* images
- 4. Entropy coding

