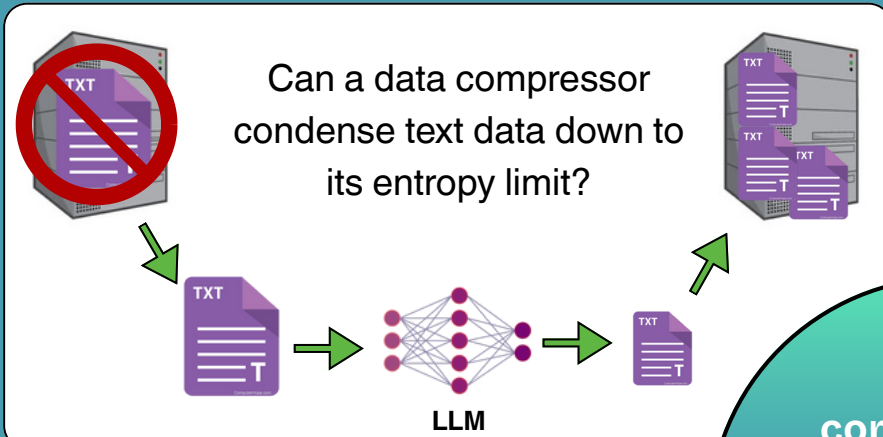


Approaching Entropy Limits with Learned Lossless Compression

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Research Question



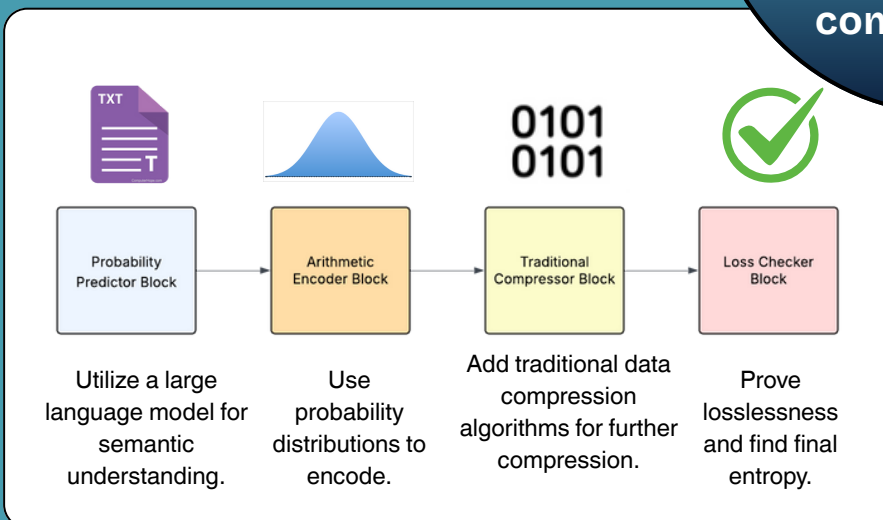
Data Analysis & Results

| Compressor | Dickens | | | | | | | Enwik9 | | |
|--------------|---------|--------------------|--------------------------|-------------|------|---------------------|----------|---------|-------|-------|
| | Default | CMix (Byron, n.d.) | TRACE (Mao et al., 2022) | 7z, bz2, xz | zst | zpaq, zlib, zip, gz | lzo, rar | Default | TRACE | 7z |
| Storage (MB) | 10 | 1.8 | 2.6 | 2.8 | 3.7 | 3.9 | 6.2 | 1000 | 185 | 225 |
| Ratio | 1 | 5.56 | 3.85 | 3.57 | 2.70 | 2.56 | 1.61 | 1 | 5.41 | 4.44 |
| % | 100% | 18% | 26% | 28% | 37% | 39% | 62% | 100% | 18.5% | 22.5% |

Neural compressors like CMIX and TRACE output greater ratios during compression; they output smaller final file sizes. Their ability to reach entropy exceeds that of traditional compressors.

Neural compression approaches entropy quicker than traditional compression.

Methodology



Conclusion

Using neural compressors, reaching entropy on large datasets is a foreseeable achievement.

Using large language models (LLMs) in conjunction with traditional models may increase accuracy of probability distributions and smaller compression.



Ollama logo: a tool that assists with running LLMs locally.