NetApp is a technology company that specializes in data storage-retrieval hardware and software systems. It maintains a repository of 65,446 technical documents, in order to provide customers with resources and instructions to efficiently use its products.

We are interested in examining how effective NetApp’s product specific documentation is in communicating technical specifications. To ensure that the documents are easily comprehensible, the company aims to build a machine learning model that can generate readability scores for each document in the corpus.

NetApp provides an XML sitemap containing HTML links corresponding to each technical document for one of the company’s products or services. All files were scraped, parsed, and stored in .txt files using Python packages Requests and BeautifulSoup. The following analysis methods were employed on this corpus:

- **Dimensionality reduction** of readability scores using linear methods, e.g. principal component analysis (PCA), and nonlinear methods, e.g. uniform manifold approximation and projection (UMAP).
- **Sparsity measure** of the documents, represented as a vector encoding the conditional distribution of an n-gram model.
- **Deep learning** methods to predict a readability score with document embeddings in a moderately high-dimensional vector space using labels generated from UMAP.

A total of 18 readability scores were extracted from the 65,446 documents, represented as vectors in $\mathbb{R}^{18}$. The 18 readability scores computed for each document contained a lot of overlapping information as seen above. We implemented PCA and UMAP to capture the principal components of the data and identify nonlinear structure within the dataset.

To capture further nonlinearities, we train a feedforward neural net on the document data. Our samples consist of doc2vec embeddings of each document with 1-dimensional labels generated from UMAP, which essentially reduces the 18 readability scores to a single scalar.

The training and testing loss deviates around certain values rather than showing consistent improvement, even with varying step sizes, optimizers, regularization parameters, and neural net size. This indicates that the document and UMAP embeddings may be uncorrelated, leading to difficulties of the neural net finding patterns. Another potential problem may be that the loss landscape may be too “jagged,” making it harder for Adam to find local minima.

We measure the sparsity of this vector using the PQ index (which is permutation-invariant) defined

$$I_P(w) = 1 - d^{1/\gamma} \frac{\|w\|_q}{\|w\|_p} \left( \sum_{i=1}^n |w_i|^q \right)^{1/\gamma}$$

A higher index indicates higher sparsity, indicating lower readability. We convert each document to a vector storing the counts of possible future words.

$$v_{doc} = (v_1, \ldots, v_j), \quad \text{where } j = \# \text{ of possible next words}$$

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The results indicate that utilizing a combination of established readability scores is useful in detecting readability of technical documentation. We are able to identify clusters and correlations between the readability features of the NetApp corpus, and further work can be done on improving the interpretability of these algorithms.

Measuring the distributional sparsity of words in the document, which is directly related to the entropy of the conditional distribution of future words, also provides insights on how the readability is distributed across the entire corpus. We found that these distributions are left-skewed, indicating that few documents are extremely easy to read, while most of the documents are either clustered towards high sparsity values near 1 or roughly follow a Gaussian distribution.

Finally, we have provided a deep learning architecture for measuring readability, which can be used in the future with higher-quality datasets containing more accurate labels on readability.

References

- E. Diao, G. Wang, Z. Yang, Y. Ding, and V. Tarokh. Pruning Deep Neural Networks from a Sparsity Perspective. ICLR 2023