



Figure 2. An example of feature clustering applied to a neuron in layer 7 of GPT2-small. The clusters (colour and numerically coded) each show a distinct semantic behaviour, and the dendrogram shows how the cluster hierarchy formed. The highlighting corresponds to neuron activation on each token, with the neuron embedding derived from the maximally activating token.

behaviour (blue) almost 50:1<sup>4</sup>. Without feature clustering, it's very easy to miss these rarer behaviours during interpretation - unless you review a large number of examples even after there appears to be a clear hypothesis for the behaviour, you would naturally conclude that this is a monosemantic neuron. Feature clustering allows us to collect a much larger number of examples and automatically condense them, making it much easier to quickly identify all the relevant behaviours of a neuron. This could help to address the illusion of interpretability (Bolukbasi et al., 2021), where examining the top examples for a neuron suggests a simple explanation of the behaviour, but expanding to lower activating examples reveals an array of hidden behaviours.

#### 4.1.3. COMPARISON TO EMBEDDINGS

Whilst we choose to use neuron embeddings to cluster a neuron's dataset examples, we could instead just use the pre-MLP embedding of the key token, without then multiplying it by the neuron's weights. Table 1 compares the median intra- and inter-cluster distances of the dataset example clusterings for all neurons in GPT2-small when using the pre-MLP embeddings or neuron embeddings. It shows that neuron embeddings lead to denser clusters with reduced intra-cluster distance, with better separation between these clusters from the increased inter-cluster distance. Figure

<sup>4</sup>The dendrogram doesn't show the full hierarchy for simplicity - some of the orange leaves are actually clusters with multiple elements

Table 1. Intra- and inter-cluster distance of embedded dataset examples averaged across all neurons in GPT2-small, comparing pre-MLP embeddings with neuron embeddings. Neuron embeddings on average result in denser clusters with better separation between clusters.

DISTANCE	INTRA-CLUSTER	INTER-CLUSTER
PRE-MLP	0.31	0.63
NEURON	0.21	0.73

4 clearly illustrates this, showing a pair of clusters with significantly higher density and separation using neuron embeddings compared to pre-MLP embeddings.

The improved separation between clusters implies that feature clusters derived from neuron embeddings will have fewer errors than those derived from pre-MLP embeddings. Anecdotally, we found this to be the case, particularly when using simpler but faster clustering algorithms such as the Sub-Cluster Component algorithm (Monath et al., 2021).

The better performance of neuron embeddings also indicate that they better capture the similarity between a neuron's dataset examples. Intuitively, this is because a neuron may not respond to all information in the pre-MLP embedding, so by incorporating the neuron weights, which represent what the neuron is "looking for" in an input, we select out the relevant information to the neuron, providing a better representation of what caused the neuron to activate.