Multiple Narrative Disentanglement
ft. identification of narrative threads in *Infinite Jest*

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Background

Complex texts usually have multiple narrative threads interwoven rather than a standard linear narrative structure. The task of multiple narrative disentanglement is performed by segmenting texts and reconstructing the separate narrative threads. It can be used for automatic plot summarization, thematic reorganization of a chronological text, and other literary analysis.

We explore several different approaches to the task, drawing from both supervised and unsupervised learning, and demonstrate them on *Infinite Jest*, the nearly-1100 page magnum opus of the late David Foster Wallace, famous for its size and complexity.

Text Feature Extraction

Our various methods for feature extraction are shown at left in Figure 3. Below, in Figure 4, we present several overlaid histograms of test errors for the four different methods of feature extraction indicated in the legend.

The bimodal distribution shows the relative improvement of a word-frequency method over a term-frequency/inverse document-frequency (TFIDF) method. We had assumed that TFIDF would produce the better test error, but since our results show otherwise, it is possible that segment length is not independent of the particular narrative thread. Moreover, the small difference in peaks in the two modes of the distribution show how using named entity extraction improved our test error.

Narrative Models

In addition to classifying the segments into their narrative thread with supervised learning algorithms, we also explored the data with two unsupervised methods.

We used Latent Dirichlet Allocation (LDA) to associate topics with groups of segments. Performing LDA on the unfiltered segments yields groups that combine narratives around female characters and those around male characters, due to the prevalence of gendered pronouns. When we performed LDA on only the named entities, the top words of each group of entities corresponded most often to characters and places who are part of the same larger narrative thread. K-means clustering showed varying degrees of similarity between clusters (Fig. 5).