Machine Learning in Computational Literary Studies
An Overview of methods and applications

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Introduction

Machine learning in its facets is an integral part of the methodological repertoire of Computational Literary Studies. Especially for the analysis of genre, period and authorship supervised and unsupervised learning has enabled researchers to base their theories on large text collections.

Unsupervised Learning

Figure 1 shows the result of a combination of the unsupervised methods Topic Modeling (Blei et al. 2013) and Dimension Reduction to examine the genre of novels due to its publisher. Topic Modeling allows to discover distribution of hundreds of topics over large collections of text. By using the share of topics in documents as features, we can shrink this information into 2-dimensional space with Uniform Manifold Approximation (McInnes and Healy 2018).

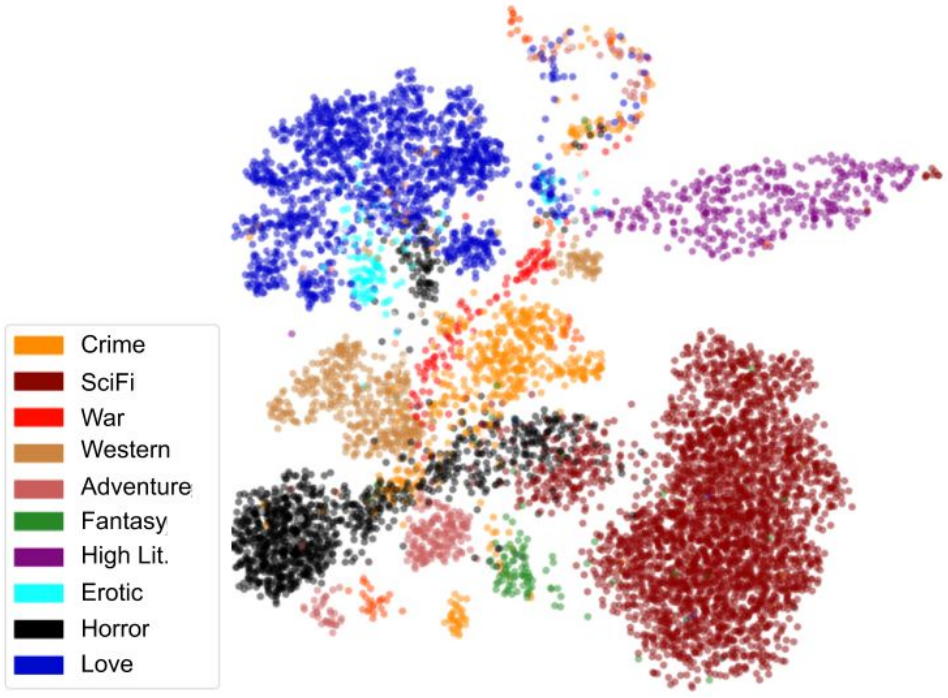

Figure 1: Genre novels plottet based on their topic proportions.

Supervised Learning

Jannidis et al. 2018 aims at overcoming inconsistent use of quotation in novels to outline direct speech by creating annotated data from a collection of texts with uniform quotation to train a neural network. In the training phase quotation is removed from the data resulting in a model predicting direct speech without relying on quotation marks.

Deep Learning and Word Embeddings

The combination of word embeddings (Mikolov 2013), Attention and Recurrent Neural Networks (Wang et. al. 2016) allows a more detailed view on the literary genres mentioned in Fig.2. While embeddings and recurrent blocks achieve a .96 f1-score on classifying the genre of segments with just 250 words, attention gives insights on which words are crucial for this decision (see Fig. 2).

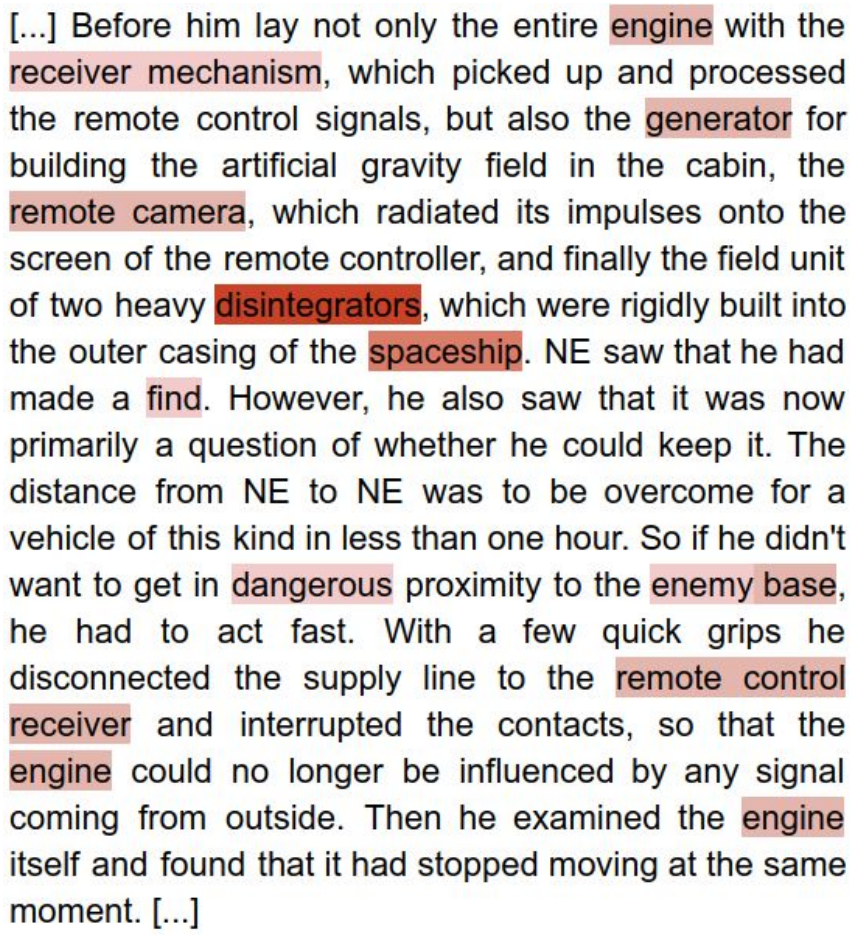

Figure 2: Segment from Kurt Mahr (1962): Perry Rhodan Band 47: *Gom antwortet nicht*. Darker red indicates higher attention of the neural network. Named Entities are replaced by NE. (Translated)

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