

Explainable NLP for Monitoring the German Automotive Industry

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Introduction

The latest developments and trends in the automotive industry, including topics such as the advance of electric cars, are of public interest and widely discussed in the news. Several online news providers have established a platform for sharing such information, and web scraping provides free access in nearly real-time.

An area with great interest is classifying large volumes of such news articles to study how the press perceives the automotive sector from a national perspective, i.e. how sentiment relates to survey studies like VDA or if it can serve as a relevant innovation indicator.

However, sentiment analysis on this data is challenging, because even if the author of an article explicitly states his/her opinion, this might not be unique across the text, but refer to some specific aspect only. Moreover, it might also involve interpretation or the use of world knowledge (Balhahur et al., 2009). In addition, to avoid getting irrelevant search results, a proper categorization of news articles into thematic categories is required.

For our application, both *accuracy* and *interpretability* are a critical concern. Generally, there is a trade-off between the benefits of interpretability associated with lexicons and the higher levels of accuracy associated with machine learning. Our goal in this study is to compare SOTA models for our task w.r.t their performance and interpretability.

Research Questions are:

- How well can we automatically classify a document as expressing a *positive, negative or neutral* opinion at the document-level
- How well can we automatically classify a document by one of the labels *Diesel, Autonomous Driving, Robotaxi, Hydrogen, Synthetic Fuel, and other*.
- Which model delivers interpretable results, highlighting words or phrases that have led to the class, and check, if this is also reflected by human rationales.

Dataset

We compile a dataset, focusing on websites of national automotive channels, a valuable source for opinionated news. The data collection currently comprises 5K German news articles, based on search queries related to the keywords *e-mobility, autonomous driving, hydrogen, robotaxi and Diesel* along with synonyms and German translations. The queries resulted in a high recall but low precision, so that the thematic category needs re-assessment.

From this data, we create a benchmark and so far annotated 350 German news articles manually w.r.t. positive/negative sentiment words as well as the overall document-level sentiment, and assessed inter-annotator agreement (IAA) using the *tagtog* platform. We achieved an IAA of 80.34% for overall sentiment classification and 88.98% for text classification.

Methodology

For the tasks *sentiment analysis* and *news categorization* we identify three conceptually distinct groups of methods: (1) lexicons, (2) traditional machine learning, and (3) transfer learning. The use of contextualized representations of words, as exemplified by the transformer model BERT (Devlin et al. 2018; Guhr et al., 2020) have advanced the SOTA performance across many tasks, including sentiment analysis (Poria et al., 2020), and news categorization (Ha, 2021) because they can capture semantic variability. In our experiments, we compare BERT, CNN, and LSTM and traditional ML approaches like SVM, and rule-based system. Moreover, we experiment with different XAI algorithms implemented in captum (Kokhlikyan et al., 2020), that seek to explain model predictions.

Preliminary Results

Document-level Sentiment Analysis: We compare different SOTA classifiers and evaluate the models on our annotated data, split into train, test and development. For example, the ML method SVM_{linear} reaches an accuracy of 53% (see Fig. 1), outperforming GerVADER (Tymann et al., 2019) with an accuracy of 50%.

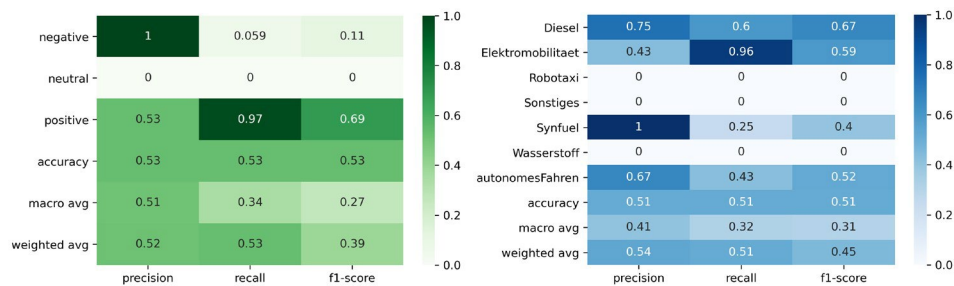


Figure 1 The evaluation results of document-level sentiment classification (left) and news categorization (right) for SVM. Since the datasets are imbalanced, we also present macro-averaged precision, recall, and F1 measure. (Note: performance results are only preliminary, since work on the benchmark corpus is still in progress.)

Explainable NLP: Deep learning models are black-box models with little explainability. Therefore, we apply various interpretation techniques to our prediction models that seek to explain their analysis results post-hoc, such as LIME and Integrated Gradients (ITO et al., 2021). To this aim, we first created a benchmark of human annotations, where salient features are highlighted within the news article. An example for a single news article of the corpus is shown below (see Fig.2, right). Then, we check for agreement between human annotations and the model's extracted rationales (see Fig2, left).



Figure 2 shows the content of the news article entitled ‘China announces massive promotion programs for electric commercial vehicles’ on e-mobility with overall positive sentiment. The human rationale is annotated in tagtog on relevant entities on the right (blue=positive, red= negative). This is compared to the output of the machine learning model (here Random Forest) on the left.

Conclusion and Outlook

In this work, we report on our methodology for creating labeled German news data, as well as applying sentiment analysis, news categorization and explainable NLP interpretation

techniques. Our main contributions focus on a discussion on the differences between SOTA sentiment detection and news categorization models for our German benchmark data w.r.t. the criteria performance and interpretability. We believe that this will help select and improve a model and/or its explanations in the long run.

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