

UNIVERSITY OF TWENTE

MASTER THESIS

TRUST IN AUTOMATED DECISION MAKING

HOW USER'S TRUST AND PERCEIVED UNDERSTANDING IS
INFLUENCED BY THE QUALITY OF AUTOMATICALLY GENERATED
EXPLANATIONS

Author:
Andrea PAPENMEIER

Supervisor:
Dr. Christin SEIFERT
Dr. Gwenn ENGLEBIENNE

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UNIVERSITY
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Abstract

1 Introduction

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Intro

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Intro

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asd definition of offensive language

2.2 Explanations

Intro

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2.3 Explanations in AI

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2.5 Summary

Summary

Hypotheses

3 Dataset

Intro

3.1 Dataset Selection

Few datasets with offensive language texts are publicly available. Table 1 presents an overview of four available datasets, their sizes and class balances. While the dataset of SwissText has the most fine-grained labelling of its data

Corpus	Size	Classes	
Davidson ¹	25,000	hate speech	6%
		offensive	77%
		neither	17%
Imperium ²	3,947	neutral	73%
		insulting	27%
Analytics Vidhya ³	31,962	hate speech	7%
		no hate speech	93%
SwissText ⁴	159,570	toxic	10%
		severe_toxic	1%
		obscene	5%
		threat	0.3%
		insult	5%
		hate speech	1%
		neither	72.7%

Table 1: Publicly available datasets for offensive language texts

points, details on how the labels were assigned (i.e. number of annotators, inter-annotator agreement score, definition of the classes) are not available. The same holds for the datasets of Analytics Vidhya and Imperium.

In contrast, Davidson’s datasets comes with a description of how the data points were collected, how the classes are defined, and uses at least three annotators per text. Furthermore, Davidson’s dataset contains the most data points labelled as offensive: roughly 20750 Tweets fall into this category, while the Analytics Vidhya dataset contains 2240 hate speech texts, SwissText 1600, and Imperium 1000.

Throughout the literature, different definitions of hate speech and offensive language are given. For using a dataset in a user study with the scenario of a social media administrator, the definition of the label has to be clear. We therefore chose to work with the dataset of Davidson et al., as it offers the most detailed description of its labels and how the labels were obtained.

3.2 Dataset Construction

The original dataset was collected by Davidson et al. [3] for their research on defining and differentiating hate speech from offensive language. They con-

structured a dataset with offensive Tweets and hate speech by conducting a keyword search on Twitter, using keywords registered in the hatebase dictionary⁵. The timelines of Twitter users identified with the keyword search were scraped, resulting in a dataset of over 8 million Tweets. They selected 25 000 Tweets at random and had at least 3 annotators from Figure Eight⁶ (formerly Crowd Flower) who labelled each Tweet as containing hate speech, offensive language, or neither. They reached an inter-annotator agreement of 0.92 [3]. The dataset is publicly available on GitHub⁷.

The biggest class in the dataset are the offensive language Tweets (77%), while non-offensive Tweets represent 17%, and hate speech 6% of the dataset.

For our research, we are only interested in offensive and not offensive Tweets. We therefore excluded Tweets labelled as hate speech for the further construction of our dataset. We produced a balanced dataset by selecting only Tweets with the maximum inter-annotator agreement from each of the two remaining classes, and randomly drew Tweets from the bigger class (offensive Tweets) until the size of the subset was equal to the size of the smaller class (non-offensive Tweets). Table 2 presents statistical information about the resulting dataset.

	Not Offensive Class	Offensive Class
Size (absolute)	4,162	4,162
Size (relative)	50.00%	50.00%
Total words	58,288	61,504
Unique words	6,437	9,855
Average words per Tweet	14.00	14.78

Table 2: Statistical characteristics of the constructed dataset

3.3 Dataset Preprocessing

Paragraph about common Tweet preprocessing

The following preprocessing steps are taken in chronological order:

1. Convert all texts to lower cases
2. Replace URLs by a dummy URL ('http://website.com/website')
3. Replace referenced user names and handles by a dummy handle ('@user-name')
4. This dataset encodes emojis in unicode decimal codes, e.g. "😀" for a grinning face. In order to keep the information contained in emojis,

⁵<https://www.hatebase.org>

⁶<https://www.figure-eight.com>

⁷<https://github.com/t-davidson/hate-speech-and-offensive-language>

each emoji is replaced by its textual description (without whitespaces to ensure unity for tokenizing)⁸.

5. Resolve contractions such as “we’re” or “don’t” by replacing contractions with their long version⁹.
6. This dataset uses a few signifiers such as “english translation” to mark a Tweet that has been translated to English, or “rt” to mark a Retweet (i.e. a response to a previous Tweet). Since those information have been added retrospectively, we discard them here and delete the signifiers from the texts.
7. Replace all characters that are non-alphabetic and not a hashtag by a whitespace
8. Replace more than one subsequent whitespace by a single whitespace

Example of a processed Tweet:
original:

```
"@WBUR: A smuggler explains how he helped fighters along the
Jihadi Highway": http://t.co/UX4anxeAwd"
```

after processing:

```
@username a smuggler explains how he helped fighters along the
jihadi highway http://website.com/website
```

⁸https://www.quackit.com/character_sets/emoji/

⁹https://en.wikipedia.org/wiki/Wikipedia:List_of_English_contractions

4 Design

Intro

4.1 Classifier

Intro

Good System L2X

Medium System Logistic Regression with binary (1 / -1) coefficients

Bad System Inverse L2X

4.2 Explanations

Intro

Good System L2X mutual information

Medium System randomly choosing k words from the words with positive (offensive) or negative (not offensive) class

Bad System Inverse good system

4.3 Graphical User Interface

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4.4 Subset Sampling

For evaluating the different system-explanation conditions, users have to experience the system. However, it is not feasible to present them with the complete testset, since it has a size of 1665 Tweets. Consequently, a subset of Tweets needs to be drawn from the testset, with a size that a human observer can understand and process within the time frame of a user study.

We furthermore aim to find 10 suitable subsets and assign participants randomly to one of the subsets, in order to reduce possible side effects from biases specific to single Tweets.

There are several requirements for the subsamples, originating from the conflict of reducing the sample for a human observer, yet still yielding a good representation of the testset and classifier:

- A class balance of the true labels similar to the testset,

- a balance of correctly to incorrectly classified data points similar to the classifier’s performance on the complete testset,
- no overlap of Tweets within the set of 10 subsets,
- a feature distribution as close to the feature distribution in the complete testset.

We set the subsample size to 15 Tweets, which is enough to show accuracies to the first decimal place, yet assumably not too much to process for an observer in a user study.

To create a subset, 15 data points are randomly drawn from the testset.

First, the class balance of the subset is calculated. The difference to the class balance of the whole testset needs to be smaller than 0.1.

Additionally, for each classifier in the user study, the prediction accuracy on the subset is compared to the prediction accuracy on the complete testset. If, for all classifiers, the difference is smaller than 0.1, the next check is performed.

To ensure the uniqueness of the subsets, the randomly drawn Tweets are compared with the content of previously found subsets. The subset is only accepted if none of the contained Tweets appear in any previously found subset.

In the last step, the feature distribution of the subset is tested against the features of the complete testset using the *Kullback-Leibler Divergence* (KLD) metric. As the focus is directed towards the explanations (i.e. the highlighted words within a Tweet), only the explanations are used to examine the feature distribution. First, the feature distribution of the complete testset is calculated by constructing a word vector with tuples of words and their respective word counts. The word counts are divided by the total amount of words in the set, such that the sum of regularised counts equals 1. Next, a copy of the word vector is used to count and regularise the word frequencies in the subset. The result are two comparable vectors, yet the vector of the subset is very likely to contain zero counts for words that appear in the complete set but were never selected as explanation in the subset. Since the KLD uses the logarithm, it is undefined for zero counts. We use Laplace smoothing with $k=1$ to handle zero counts. For each classifier, the KLD is calculated and summed to a total divergence score for the subset.

We generate a quantity of 100 such subsets and order them by their KLD sum. The 10 subsets with the smallest score are chosen as the final set of subsets.

5 Experiment 1: Explanation Evaluation

5.1 Method

Intro

5.2 Results

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6 Experiment 2: Trust Evaluation

Intro

6.1 Method

Intro

Participants

- amount, mean age, SD age
- recruitment method
- exclusion criteria
- compensation for participation

Apparatus A paragraph about the experiment setup (physically), system requirements and technology used. For example the pixel dimensions of screen-shots.

Procedure

- tasks / survey items
- ordering of tasks

Design & Analysis One paragraph for experiment design (statistically).

One paragraph for statistical analysis.

- data points per participant and in total
- statistical test
- corrections / disqualifications

6.2 Results

Intro

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7 Discussion

8 Conclusion

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References

- [1] Hiva Allahyari and Niklas Lavesson. User-oriented assessment of classification model understandability. In *11th scandinavian conference on Artificial intelligence*. IOS Press, 2011.
- [2] Leila Arras, Franziska Horn, Grégoire Montavon, Klaus-Robert Müller, and Wojciech Samek. " what is relevant in a text document?": An interpretable machine learning approach. *PloS one*, 12(8):e0181142, 2017.
- [3] Thomas Davidson, Dana Warmley, Michael Macy, and Ingmar Weber. Automated hate speech detection and the problem of offensive language. In *Proceedings of the 11th International AAAI Conference on Web and Social Media*, ICWSM '17, pages 512–515, 2017.