Empower Fruitful Discussions

Ksenia Gerasimovich, Daniel Guhr, Katharina Neumüller & Kristin Stöcker





Dr. Daniel GuhrPhysicist
Data Scientist

My Background

PhD Physics, Univ. of Constance System Engineer Project manager

Looking for projects (freelancer) as

- □ Data Scientist
- □ Data Analyst

remote



Ksenia GerasimovichData Scientist
Consultant

My Background

Business Informatics B.Sc. Finance MBA Business analyst Consultant: ERP, BI implementation

Looking for a job as

- □ Data Scientist
- □ Data Analyst

in Düsseldorf oder remote



Katharina Neumüller Data Scientist

My Background

Computational Linguistics B.Sc. Web-Development Project Management

Looking for a position as

- □ Data Scientist
- □ Data Analyst

in Cologne or remote



Kristin Stöcker Linguist Data Scientist

My Background

M.A. Linguistics Research Assistant at FU Berlin

Looking for a job as

- □ Data Scientist
- **□ Data Analyst**
- □ Data Engineer

in NLP

in Berlin or remote

Attention

Trigger Warning

This presentation contains examples of profane, vulgar or offensive language that is likely to upset readers!

The Background

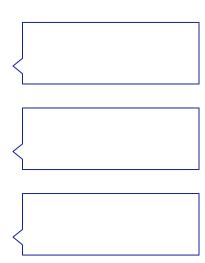
The perks of online communication

free speech/
anonymity

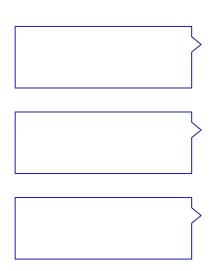
exchange of opinions

independent of time
and location





The price of online communication





41% of US adults experienced online harassment*

30% of affected users stopped using an online service*

27% of witnesses refrained from posting online*

Consequences for website operators

- content moderation presents enormous financial burden
- result: disabled comment sections
- New York Times: only 10% of articles allowed comments (before 2016)
- How can Al help to counter this problem?







Application of Perspective API in online communication

"Shut up. You're an idiot!"

Toxicity 0.99

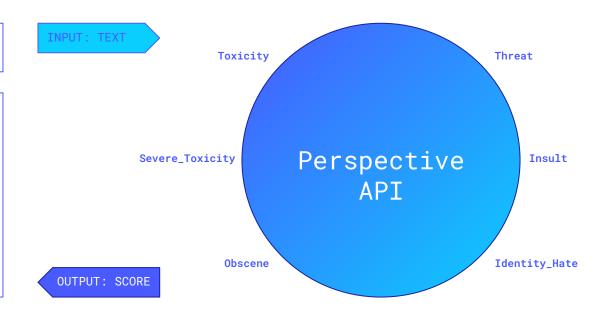
Severe_Toxicity 0.81

Obscene 0.20

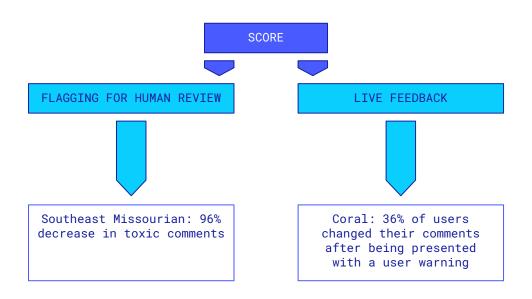
Threat 0.09

Insult 0.97

Identity_Hate 0.02



One API, many applications



Toxic Comment Classification Challenge

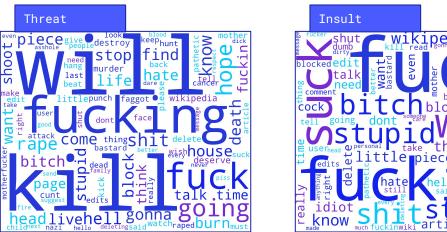
- goal: multi-headed model capable of detecting different types of toxicity like threats, obscenity, insults, and identity-based hate
- dataset of 160.000 comments from Wikipedia's talk page edits
- train data labelled by humans



The Data







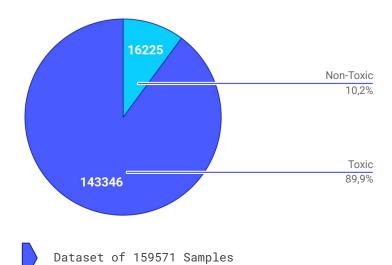




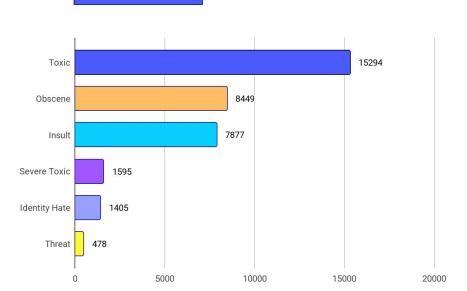


Data

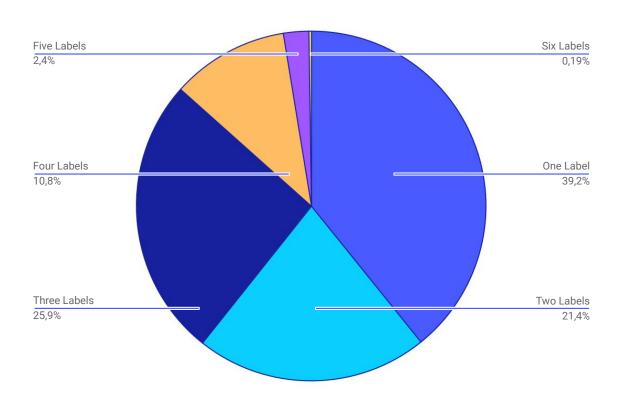




Category Counts

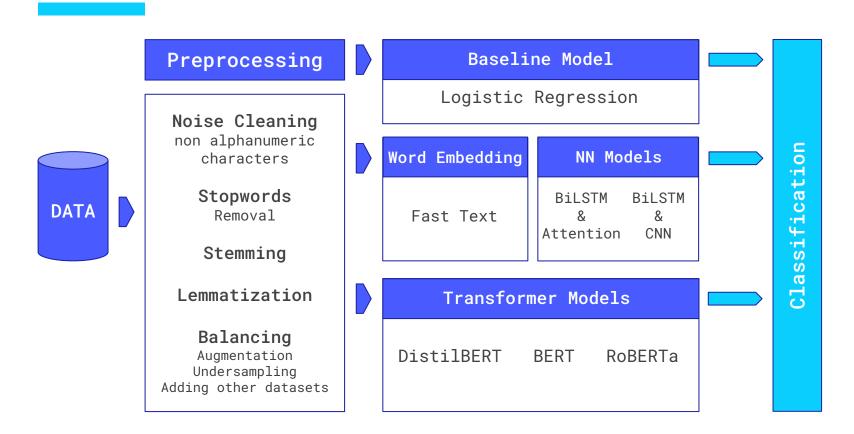


Comments with multiple labels



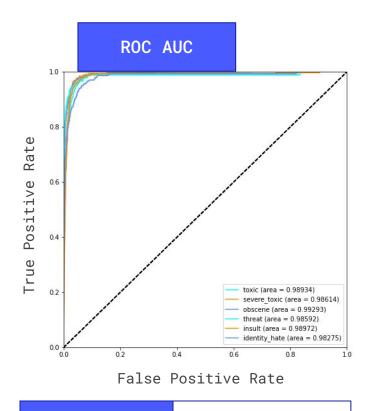
Approach & Results

A Modular Approach



RoBERTa Classification Results

labels	precision	recall	f1-score	support
toxic	0.94	0.90	0.92	3102
severe_toxic	0.60	0.45	0.51	345
obscene	0.86	0.91	0.88	1772
threat	0.64	0.69	0.66	102
insult	0.78	0.88	0.83	1613
identity_hate	0.65	0.72	0.69	277
micro avg	0.85	0.87	0.86	7211
macro avg	0.75	0.76	0.75	7211



mean column-wise **ROC AUC**

train 0.98780

test

0.98482

Error Analysis

Contextual Issues

"I'm glad you have gone do not come back"

Category	True	Predicted
toxic	1	0
severe_toxic	0	0
obscene	0	0
threat	0	0
insult	0	0
identity_hate	0	0

PROBLEM

Lack of context in training samples

SOLUTION

Additional labeling of comments with frequent word repetitions and retraining



Subjectivity in labelling

"And I know I am a dickhead"

Category	True	Predicted
toxic	1	1
severe_toxic	0	0
obscene	1	1
threat	0	0
insult	1	0
identity_hate	0	0

PROBLEM Correct model predictions

Label Assignment Error

Pseudolabelling

SOLUTION

Lack of profanity and context to train the model

"islams you motha fers"

Category	True	Predicted
toxic	1	1
severe_toxic	1	0
obscene	1	0
threat	0	0
insult	1	1
identity_hate	0	1

PROBLEM

Context awareness exists, but in insufficient volume

SOLUTION

More samples for training

Context Awareness: Insults on political and religious grounds

Outlook

- Try out other Transformers XLNet
- More training data (from other sources like Twitter)
- Further fine-tuning
- Ensemble models
- Out-Of-Vocabulary Words
 - Training own embeddings

Thank you

Questions, comments and discussions are welcome.

Back up

Error analysis: Possible solution approaches

Contextual issues:

-> Additional labeling of comments with frequent word repetitions and retraining

Subjectivity in the case of labelling:

-> Pseudolabelling

00V words (Lack of profanity and context to train the model):

- -> Training own embeddings
- -> TODO Add this point to outlook

Error Analysis

Lack of profanity and context to train the model

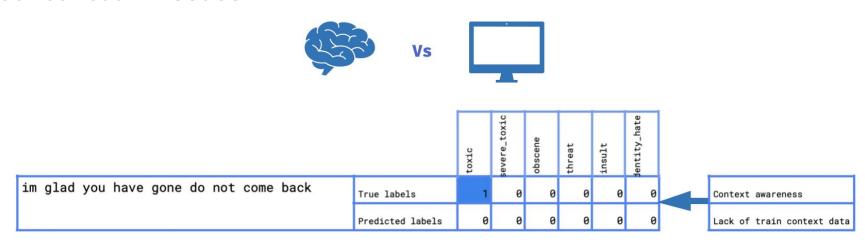


Context awareness: insults on political and religious grounds Context awareness exists, but in insufficient volume

1

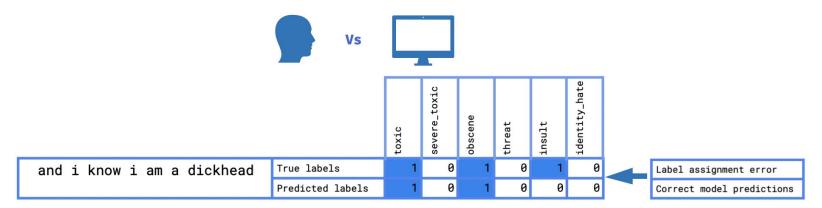
Error Analysis

Contextual issues

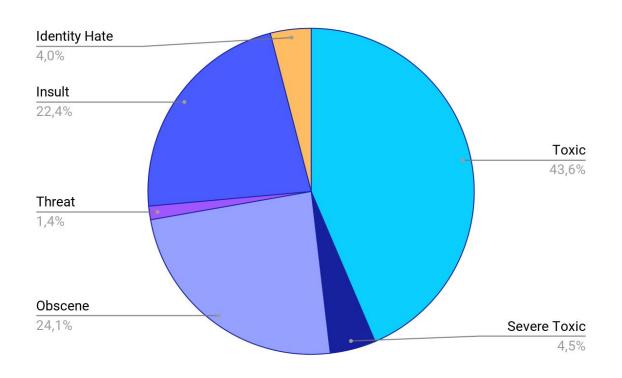


Error Analysis

Subjectivity in the case of labelling



Category Count - Pie Chart

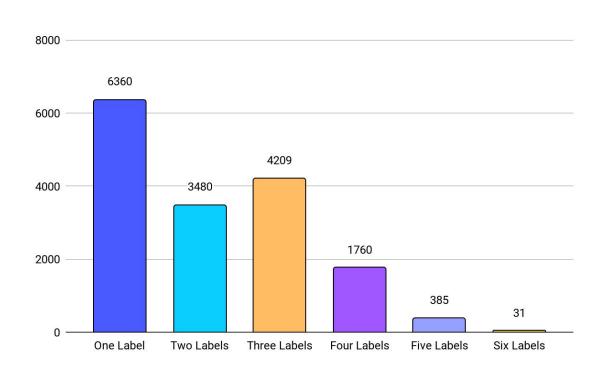


Benchmark models

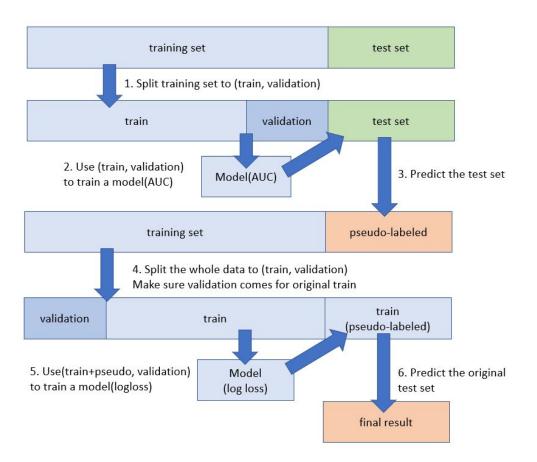
1st	.9885	RNN (BiGru)	 ✓ Diverse pre-trained embeddings ✓ train and test-time augmentation (TTA) using translations to other language ☐ Train on translation ✓ Pseudolabelling ✓ Enssembling ✓ Averaging ✓ Stacking ☐ Feature engineering ☐ Training own embeddings for OOV words
neongen 2nd place	.9882	RNN, DPCNN and GBM	 ✓ Diverse pre-trained embeddings ✓ train and test-time augmentation (TTA) using translations to other language ✓ Train on translation ☐ Pseudolabelling ✓ Enssembling ✓ Averaging ☐ Stacking

https://www.youtube.com/watch?v=_-VeZU4JyBo

Comments with multiple labels - Bar Chart

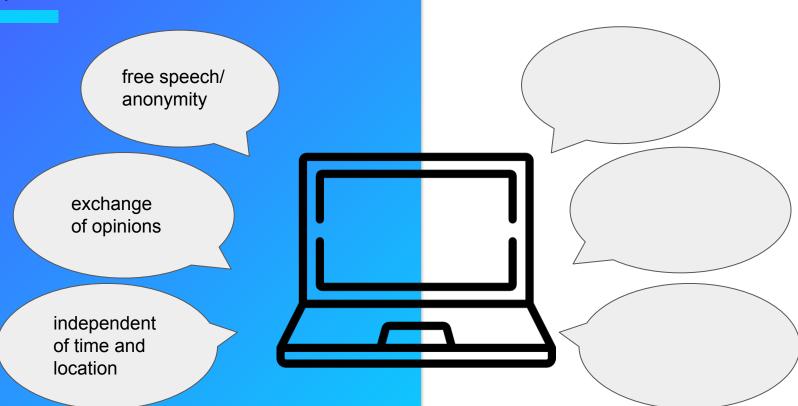


Pseudolabelling

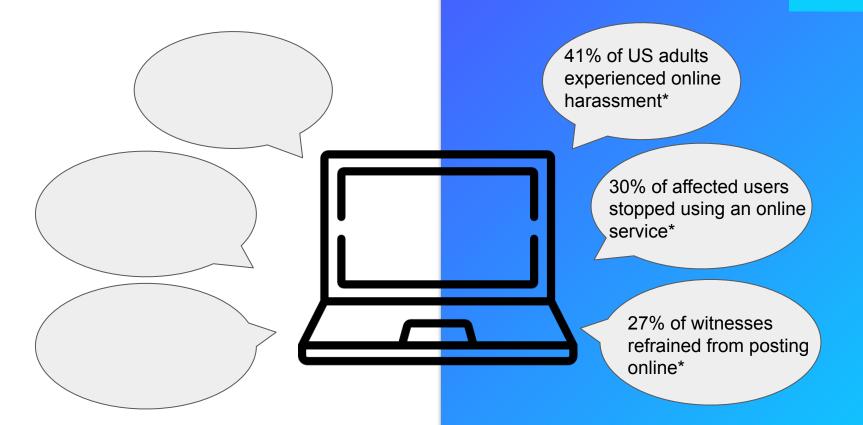


https://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge/discussion/52557

the perks of online communication



the price of online communication



consequences for website operators



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Toxic Comment Classification Challenge

- goal: multi-headed model capable of detecting different types of toxicity like threats, obscenity, insults, and identity-based hate
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P Featured Prediction Competition

Toxic Comment Classification Challenge

Identify and classify toxic online comments

\$35,000

Prize Money