Detection of Antisocial Behavior in Online Communities

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Online communities

- social networks, knowledge sharing systems, online games, news and entertainment portals
- hundreds of millions people in the world
- user generated content
- antisocial behavior: haters, trolls, flamers, spammers, cyberbullies
- regulated mainly by moderators goal is to make their job easier

Detection of content containing hate in YouTube comment sections



Data acquisition

- over 200 000 comments collected from political YouTube channel The Young Turks
- YouTube API + JavaScript

Labeling of data



- over 6 000 comments chosen for labeling
- crowdsourcing via custom Django app
- 700 comments labeled as either hateful or benign by 24 participants
- weighted average Fleiss kappa of 0.6813

Classification using machine learning

• data preprocessing – lemmatization, stopwords removal



- feature extraction (extracted 117 features, 64 of them used in classification)
- min-max normalization, oversampling
- different supervised classifiers
- k-fold validation
- parameter tuning
- problem not enough labeled data
- co-training semi-supervised machine learning method

Our method for automatic detection of antisocial behavior

- existing solutions differ in platforms, type of behavior that is being detected, utilized algorithms and used features detection of antisocial users vs. detection of inappropriate content
- machine learning based approach different categories of features:
- textual features (including sentiment analysis)
- o features of user history
- o community reaction
- hierarchical data
- our hypothesis: by combining features from all feature categories, the ability to detect antisocial behavior increases

Co-training

- two classifiers use two different sets of features • feature sets must be independent and uncorrelated
- co-training uses unlabeled data to construct new labeled data for future iterations





Results **Supervised classifiers**

Co-training

- data)
- algorithm
- possible



0.25

Type of classification

- ERT textual features + h
- ERT user history + comr

ERT – all

co-training (with highest I

Conclusion

- improve performance of classifiers



• best results with Extremely randomized trees classifier (ERT) • classification using different combinations of feature categories:

• best combination of classifiers and feature sets:

I. Extremely randomized trees (textual features + hierarchical

2. AdaBoost (user history features + community reaction) results vary for different parameter settings of co-training

our goal is to maximize recall, yet still keep precision as high as

0,35 pre	0,45 cision	0,55	
	Precision	Recall	F ₁ -score
ierarchical data	39.24 %	55.53 %	45.13 %
nunity reaction	39.30 %	57.80 %	46.02 %
	45.76 %	58.00 %	50.00 %
F ₁ -score)	46.34 %	64.71 %	53.56 %

• results confirm, that combination of all feature categories trains a classifier better then a subset of these categories • we also demonstrated the capability of co-training algorithm to