Can We Hide in the Web?

DIPF Bildungsforschung und Bildungsinformation

Age and Gender Author Profiling in Social Media

.most of this sugar comes from high fructose corn syrup which is the chief ingredient in chips, cereals or breads. And just because it is "all natural", it does not mean it's good for you. To the body, it's all sugar!

Was this text written by a...



DKPro Text Classification & WEKA

Multiclass classification for six classes

(one-against-all approach)

Information Gain filter



System Setup - DKPro Lab Framework

PAN Challenge Data

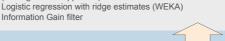


- from web environment (chats, blogs, fora)
- 236 600 documents in English
- 75 900 documents in Spanish
- 3 age groups (13-17, 23-27, 33-47 years)
- male and female authors
- over 200 mil. words

Extracting Features DKPro Text Classification

Classification

- Long/short words, words per sentence, number of hyperlinks, number of smileys, type-token ratio, text length... Readability: Flesch, Kincaid, Coleman-Liau, SMOG, FOG, LIX
- Content: Emotion words (e.g. anger), topic words (e.g. school)
- **Syntax:** POS ratios, Contextuality measure, plurals, modals **Punctuation:** Inner punctuation, questions, exclamations
- Emotional endings (e.g. -ous, -ly...)





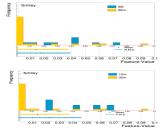
- + Ubiquitous Knowledge Processing Lab (UKP-DIPF), German Institute for Educational Research and Educational Information
- ^ Ubiquitous Knowledge Processing Lab (UKP-TUDA), Department of Compute Science, Technische Universität Darmstadt

Text Processing DKPro Core

- XML parsing
- Tokenization
- POS Tagging TreeTagger
- Lemmatizing TreeTagger Chunking Stanford Parser
- Named Entity Recognition Stanford NER

Age and gender differences are related

Style becomes more "male" with age - we get more descriptive while showing less emotions. For relevant features, such as frequency of smileys, the difference between adult men and women (upper plot) is similar to the one between teenage and adult men (lower plot).



Content-based features outperform style

Features based on word lists (mainly teenage slang and emotions) contributed to the overall performance more than stylistic features. However, they were more successful in determining age than gender.

Word list	Words	Example		
Teenage words	117	Bro, geez, tonite, lol		
People words	134	Relative, team-mate, friend		
Work words	287	Employee, bonus, recruiter		
Positive words	297	Cheerful, amused, joyful		
Negative words	507	Miserable, scared, stressed		

Performance (classifier accuracy)

Subsystem	English	Spanish	
Maj.class baseline	0.17	0.17	
Human evaluation	0.25	-	
Surface features only	0.20	0.21	
Syntactic & punct.features	0.23	0.30	
Content & lexical features	0.27	0.33	
Syntax.& punct.& content & lex.	0.29	0.38	
All features combined	0.29	0.38	

EN gen.	EN age	EN all	ES gen	ES age	ES all
0.5	0.33	0.17	0.5	0.33	0.17
0.5	0.55	0.25	-	-	-
0.58	0.53	0.29	0.65	0.57	0.38
	gen. 0.5 0.5	gen. age 0.5 0.33 0.5 0.55	gen. age all 0.5 0.33 0.17 0.5 0.55 0.25	gen. age all gen 0.5 0.33 0.17 0.5 0.5 0.55 0.25 -	gen. age all gen age 0.5 0.33 0.17 0.5 0.33 0.5 0.55 0.25 - -

User study

- 20 participants.
- 20 random texts from the PAN challenge
- Age accuracy 0.55, no teenagers identified
- Gender accuracy 0.5 = random decisions
- Human prediction based on stereotypes, fails on neutral topics

Conclusions - Gender classification (a = .62)

Men

use longer words, more articles and hyperlinks, and talk more often about computers. Women

use more emotional words. smileys, exclamations and "love" words

Conclusions - Age classification (a = .55)

use longer words, commas, links, talk more about work and god.

Teenagers

use more pronouns and smileys, less nouns and articles, speak with more emotional words, neologisms and slang, talk more about people and computers and often violate the spelling rules.

References

Lightweight Framework for Reproducible Parameter Sweeping in Information Retrieval Richard Eckart de Castilho and Iryna Gurevych, In: Maristella Agosti and Nicola Ferro and Costantino Thanos: Proceedings of the 2011 workshop or Data infrastructurEs for supporting information retrieval evaluation, vol. DESIRE '11, p. 7-10, ACM, October 2011. ISBN 978-1-4503-0952-3.

Can We Hide in the Web? Large Scale Simultaneous Age and Gender Author Profiling in Social Media -Notebook for PAN at CLEF 2013

Lucie Flekova and Iryna Gurevych, In: CLEF 2013 Labs and Workshops - Notebook Papers, p. (to appear), Septi

Older authors

write less readable longer posts,