Author profiling

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What is author profiling?

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 author profiling deals with determining author's personality and identity based on written texts

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Tasks:

What is author profiling?

 author profiling deals with determining author's personality and identity based on written texts

Tasks:

- age-group (classification)
- gender (classification)
- personality traits (regression)
 - extraversion, stability, agreableness, conscientiousness, openness to experience

Dataset:

Dataset:

- PAN competition
- 4 languages: English, Spanish, Italian and Dutch

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Approach

Approach:

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Approach:

- text preprocessing
- feature extraction
- feature selection, finding the optimal model
- evaluate the model on the test set

Preprocessing tweets

Preprocessing tasks:

Preprocessing tweets

Preprocessing tasks:

- substituting url with URL tag
- substituting usernames (referenced in replies) with REPLY tag
- removing stop words from set of user tweets
- converting all tweets to lowercase
- trimming consecutive repetitions of a letter in words (e.g 'cooool' to 'coool')

Set of features

Features used for this problem:

Set of features

Features used for this problem:

- tf-idf vectorized tweets
- number of emoticons, replies, hashtags, ...
- average length and standard deviation of posts and words respectively

Overview of additional features

Table: Overview of additional features values for each age-group, per language.

Language	English				
Age-group	18-24	25-34	35-49	50-XX	
Post length	60.714	85.853	86.680	93.753	
Post length deviation	29.656	29.401	29.532	32.192	
Word length	4.908	5.984	6.312	6.013	
Word deviation	3.493	4.726	5.088	4.452	
Emoticon count	0.057	0.064	0.046	0.038	
Hashtags	0.127	0.658	0.267	0.514	
Character repetitions	0.040	0.012	0.017	0.003	
Exclamation marks	0.137	0.207	0.195	0.527	
User replies	0.492	0.540	0.632	1.293	

Overview of additional features

Table: Overview of additional features values for each age-group, per language.

Language	Spanish				
Age-group	18-24	25-34	35-49	50-XX	
Post length	75.728	85.246	92.804	101.991	
Post length deviation	31.377	31.234	30.719	29.200	
Word length	4.935	5.295	5.647	5.409	
Word deviation	3.356	3.882	4.230	3.963	
Emoticon count	0.135	0.104	0.053	0.030	
Hashtags	0.168	0.340	0.259	0.231	
Character repetitions	0.065	0.022	0.030	0.022	
Exclamation marks	0.183	0.244	0.257	0.276	
User replies	0.579	0.715	0.818	0.854	

Overview of additional features values for gender

Table: Overview of additional features values for gender, per language.

Language	Eng	lish	Spanish		
Gender	Female Male		Female	Male	
Post length	76.786	77.222	86.030	86.949	
Post length deviation	31.131	32.908	30.594	29.574	
Word length	5.529	5.718	5.328	5.281	
Word length deviation	4.187	4.385	3.916	3.786	
Emoticons count	0.075	0.039	0.082	0.102	
Hashtags	0.380	0.394	0.357	0.190	
Character repetitions	0.026	0.020	0.041	0.025	
Exclamation marks	0.275	0.133	0.252	0.221	
User replies	0.641	0.548	0.745	0.698	

Overview of results of age-group classification per language

Table: Overview of additional features values for gender, per language.

Language	ltal	ian	Dutch		
Gender	Female	Male	Female	Male	
Post length	91.555	87.513	77.442	77.239	
Post length deviation	32.908	30.594	29.574	30.829	
Word length	5.898	6.153	5.255	5.229	
Word length deviation	4.202	4.705	3.489	3.476	
Emoticons count	0.214	0.072	0.119	0.072	
Hashtags	0.540	0.700	0.424	0.120	
Character repetitions	0.008	0.006	0.026	0.016	
Exclamation marks	0.228	0.168	0.271	0.121	
User replies	0.725	0.556	0.647	0.909	

Model used for classification:

Model used for classification:

- Logistic Regression
- Naive Bayes Classifier
- Decision Tree Classifier
- Random Forest Classifier
- SVC (using rbf, linear, poly and sigmoid kernels)

Model used for regression:

Model used for regression:

- Linear Regression
- Decision Tree Regressor
- Random Forest Regressor
- SVR (using rbf, linear, poly and sigmoid kernels)

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Testing

Testing:

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Testing:

- official test set unavailable (due to the ongoing competition)
- subset for training (70%) and testing (30%)
- 10-fold cross-validation

Results

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Overview of results

Table: Overview of results of age-group classification per language. Baseline scores are given for comparison

Language	Acc.	Prec.	Rec.	F1 ^(micro)	F1 ^(macro)
	0.782			0.652	0.782
English (baseline)	0.326	0.081	0.250	0.122	0.326
Spanish	0.933	0.975	0.900	0.924	0.933
Spanish (baseline)	0.600	0.150	0.250	0.187	0.600

Overview of results

Table: Overview of results of gender classification per language. Baseline scores are given for comparison

Language	Accuracy	Precision	Recall	F1
English	0.956	0.888	1.000	0.941
English (baseline)	0.347	0.347	1.000	0.516
Spanish	1.000	1.000	1.000	1.000
Spanish (baseline)	0.400	0.400	1.000	0.571
ltalian	1.000	1.000	1.000	1.000
Italian (baseline)	0.416	0.000	0.000	0.000
Dutch	1.000	1.000	1.000	1.000
Dutch (baseline)	0.454	0.454	1.000	0.625

Overview of results

Table: Overview of RMSE of personality traits regression per language. Baseline scores are given for comparison

Language	Extra	Stab	Agree	Consc	Open
English	0.122	0.179	0.153	0.140	0.130
English (baseline)	0.164	0.235	0.182	0.167	0.155
Spanish	0.080	0.143	0.103	0.155	0.131
Spanish (baseline)	0.123	0.220	0.149	0.211	0.183
Italian	0.048	0.123	0.067	0.086	0.099
Italian (baseline)	0.136	0.166	0.116	0.162	0.162
Dutch	0.087	0.112	0.129	0.064	0.041
Dutch (baseline)	0.137	0.197	0.155	0.115	0.116

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Conclusion

- We succeeded to obtain results similar to other published works.
- Possible upgrade:
 - Latent Semantic Analysis

The End

Questions??