

Author Profiling

Cross-genre evaluation

PAN-AP-2016 CLEF 2016
Évora, 5-8 September

Introduction

Author profiling aims at identifying **personal traits** such as **age**, **gender**, personality traits, native language... from writings.

This is crucial for:

- Marketing
- Security
- Forensics



Task goal

To investigate the effect of the **cross-genre** evaluation in the **age** and **gender** identification task.

Three languages:



English



Spanish



Dutch

Corpus

ENGLISH /
SPANISH

	Training (Twitter)		Early birds (Social Media)		Test (Blogs)		
	English	Spanish	English	Spanish	English	Spanish	
Gender							
Male vs. Female	18-24	26	16	70	16	10	4
Age Groups	25-34	136	64	92	20	24	12
	35-49	182	126	102	16	32	26
18-24; 25-34; 35-49; 50+	50-64	78	38	80	8	10	10
	65+	6	6	4	4	2	4
	Σ	428	250	348	64	78	56

DUTCH

Gender
Male vs. Female

Training (Twitter)	Early birds (Reviews)	Test (Reviews)
384	50	500

Evaluation measures

The **accuracy** is calculated per task and language.

Then, the averages per task are calculated:

$$\overline{gender} = \frac{gender_en + gender_es + gender_nl}{3}$$

$$\overline{age} = \frac{age_en + age_es}{2}$$

$$\overline{joint} = \frac{joint_en + joint_es}{2}$$

Finally, the ranking is the global average:

$$ranking = \frac{\overline{gender} + \overline{age} + \overline{joint}}{3}$$

Statistical significance

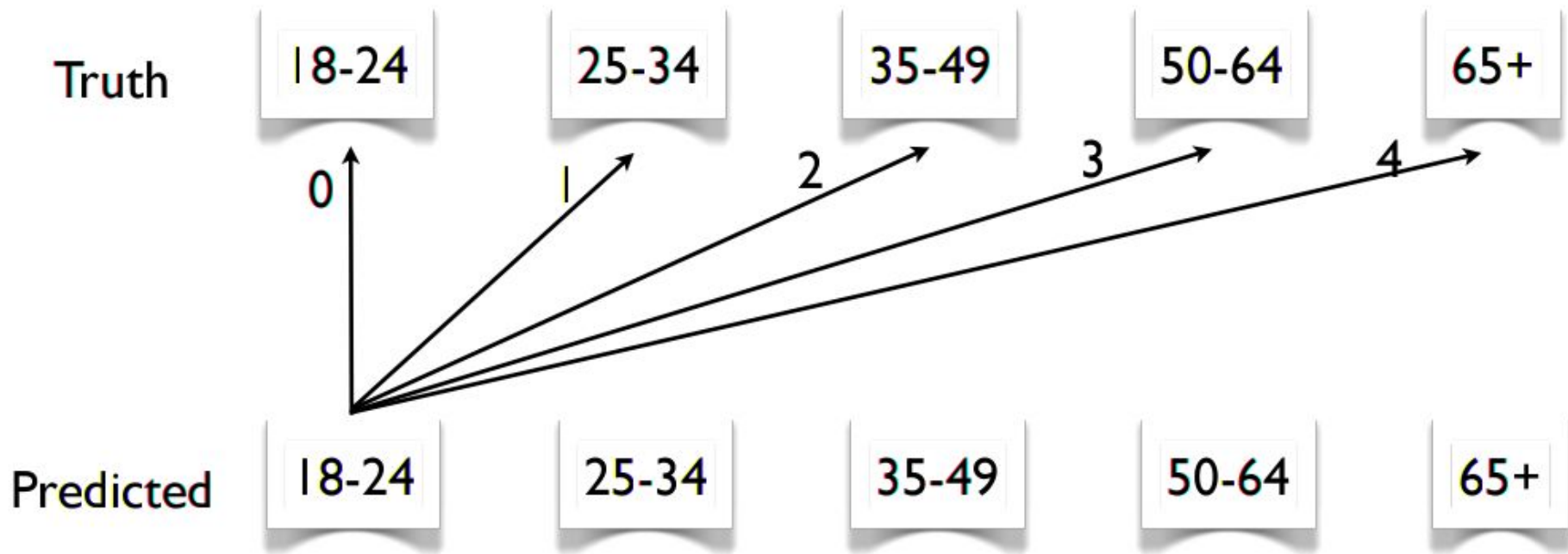
Approximate randomisation testing*

*Eric W. Noreen. Computer intensive methods for testing hypotheses: an introduction. Wiley, New York, 1989.

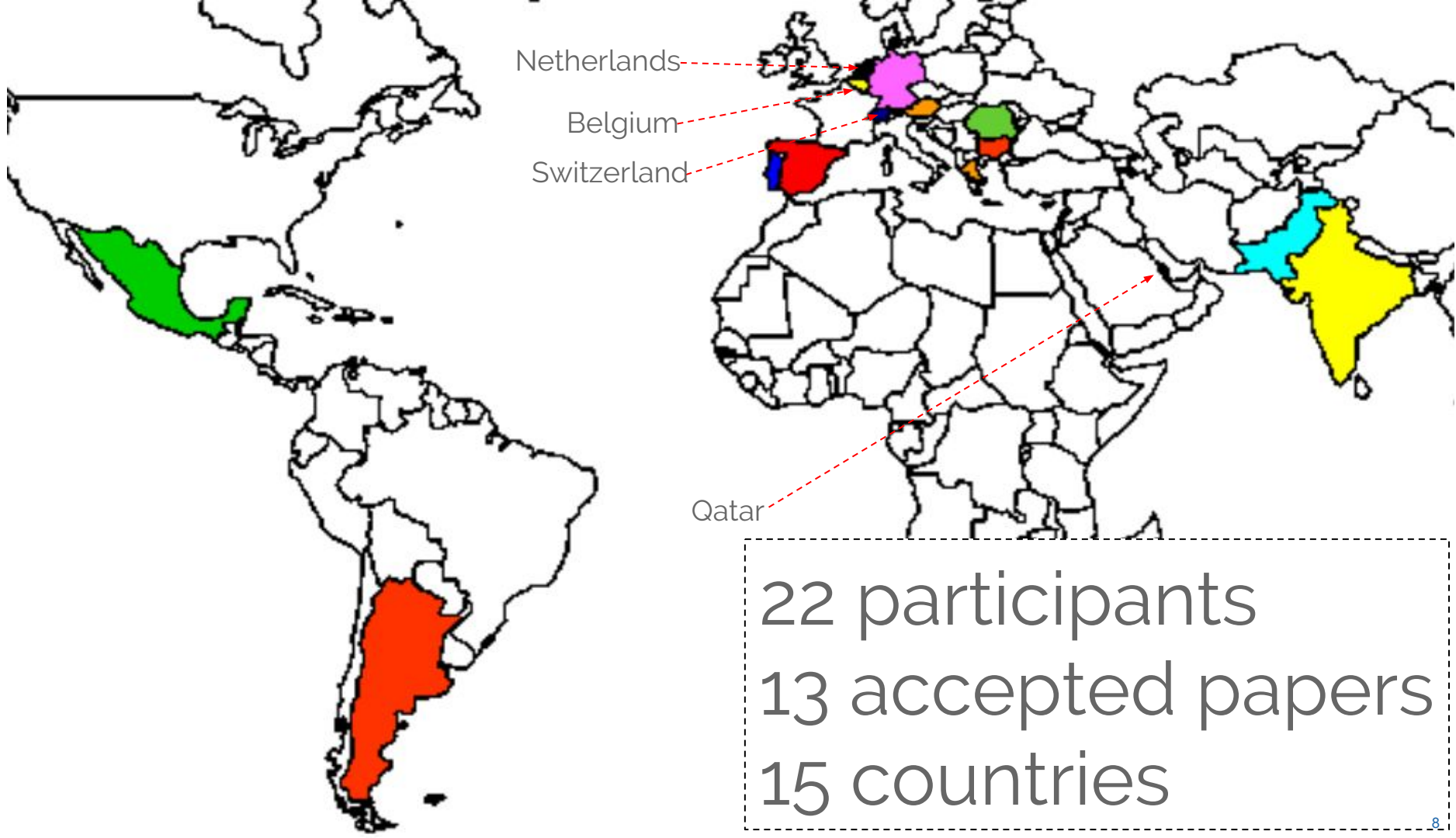
Pairwise comparison of accuracies of all systems

$p < 0.05 \rightarrow$ the systems are significantly different

Distances in age misidentification



- ▶ Missing predictions penalised with distance equal to 5
- ▶ Standard deviation of all the individual distances



Approaches

What kind of ...

Preprocessing

Features

Methods

... did the teams perform?

Approaches - Preprocessing

HTML cleaning to obtain plain text	Devalkeener, Ashraf <i>et al.</i> , Bilan & Zhekova, Garciarena <i>et al.</i>
Lemmatization (no effect)	Bougiatiotis & Krithara
Stemming	Bakkar <i>et al.</i>
Punctuation signs	Bougiatiotis & Krithara, Gencheva <i>et al.</i> , Modaresi <i>et al.</i>
Stop words	Agrawal & Gonçalves, Bakkar <i>et al.</i>
Lowercase	Agrawal & Gonçalves, Bougiatiotis & Krithara
Digits removal	Bougiatiotis & Krithara, Markov <i>et al.</i>
Twitter specific components: hashtags, urls, mentions and RTs	Agrawal & Gonçalves, Bougiatiotis & Krithara, Markov <i>et al.</i> , Bilan & Zhekova, Kocher & Savoy, Gencheva <i>et al.</i>
Feature selection (no effect)	Ashraf <i>et al.</i> , Gencheva <i>et al.</i>
Transition point techniques	Markov <i>et al.</i>

Approaches - Features

<p>Stylistic features:</p> <ul style="list-style-type: none"> - Frequency of function words - Words out of dictionary - Slang - Capital letters - Unique words 	<p>Busger <i>et al.</i>, Ashraf <i>et al.</i>, Bougiatiotis & Krithara, Bilan & Zhekova, Gencheva <i>et al.</i>, Modaresi <i>et al.</i>, Pimas <i>et al.</i></p>
<p>Specific sentences per gender</p> <ul style="list-style-type: none"> - My wife, my man, my girlfriend... <p>And per age</p> <ul style="list-style-type: none"> - “I’m” followed by a number 	<p>Gencheva <i>et al.</i></p>
<p>Sentiment words</p>	<p>Gencheva <i>et al.</i>, Pimas <i>et al.</i></p>
<p>N-gram models</p>	<p>Ashraf <i>et al.</i>, Bougiatiotis & Krithara, Modaresi <i>et al.</i>, Bilan & Zhekova, Gencheva <i>et al.</i>, Garciarena <i>et al.</i>, Markov <i>et al.</i></p>
<p>Parts-of-speech</p>	<p>Bilan & Zhekova, Busger <i>et al.</i>, Gencheva <i>et al.</i>, Ashraf <i>et al.</i></p>
<p>Collocations</p>	<p>Bilan & Zhekova</p>

Approaches - Features

LDA	Bilan & Zhekova
Different readability indexes	Gencheva <i>et al.</i>
Vocabulary richness	Ashraf <i>et al.</i>
Correctness	Pimas <i>et al.</i>
Verbosity	Dichiu & Rancea
Second order representation [22]	Busger <i>et al.</i> , Bougiatiotis & Krithara, Markov <i>et al.</i>
Bag-of-words	Devalkeener, Kocher & Savoy, Bakkar <i>et al.</i>
Tf-idf n-grams	Agrawal & Gonçalves, Dichiu & Rancea
Word2vec	Bayot & Gonçalves

Approaches - Methods

Random Forest	Ashraf <i>et al.</i> , Pimas <i>et al.</i>
J48	Ashraf <i>et al.</i>
LADTree	Ashraf <i>et al.</i>
Logistic regression	Modaresi <i>et al.</i> , Bilan & Zhekova
SVM	Bilan & Zhekova, Dichiu & Rancea, Bayot & Gonçalves, Markov <i>et al.</i> , Bougiatiotis & Krithara, Bakkar <i>et al.</i> , Busger <i>et al.</i>
SVM + bootstrap	Gencheva <i>et al.</i>
Stacking	Agrawal & Gonçalves
Class-RBM	Devalkeneer
Distance-based approaches	Kocher & Savoy, Garciarena <i>et al.</i>

Early birds evaluation in social media (EN/ES)

English			
Team	Joint	Gender	Age
Waser*	0.2098	0.5230	0.3879
Busger <i>et al.</i>	0.1897	0.5575	0.3046
Devalkeneer	0.1839	0.5259	0.2931
Dichiu & Rancea	0.1753	0.5345	0.2989
Agrawal & Gonçalves	0.1724	0.5431	0.3103
Bougiatiotis & Krithara	0.1724	0.5345	0.3046
Modaresi(a)	0.1724	0.5057	0.3218
Bilan <i>et al.</i>	0.1667	0.5374	0.2902
Gencheva <i>et al.</i>	0.1638	0.5287	0.2902
Garciarena <i>et al.</i>	0.1609	0.5201	0.2816
Kocher & Savoy	0.1552	0.5144	0.2816
Modaresi <i>et al.</i>	0.1552	0.5029	0.3017
Zahid	0.1523	0.4885	0.3103
Ashraf <i>et al.</i>	0.1494	0.4971	0.2902
Roman-Gomez	0.1494	0.5144	0.2874
Bakkar <i>et al.</i>	0.1466	0.5029	0.2874
<i>baseline</i>	0.1207	0.5402	0.2126
Pimas <i>et al.</i>	0.0057	0.0201	0.0086

Spanish			
Team	Joint	Gender	Age
Bougiatiotis & Krithara	0.2031	0.5781	0.3438
Kocher & Savoy	0.2031	0.5000	0.3125
Modaresi <i>et al.</i>	0.2031	0.6406	0.2813
Busger <i>et al.</i>	0.1875	0.5313	0.2813
Devalkeneer	0.1875	0.5625	0.3594
Garciarena <i>et al.</i>	0.1875	0.5625	0.2969
Waser*	0.1875	0.7031	0.2813
Dichiu & Rancea	0.1719	0.5469	0.2813
Gencheva <i>et al.</i>	0.1563	0.6250	0.2656
Bilan <i>et al.</i>	0.1406	0.5781	0.2969
Modaresi(a)	0.1406	0.6250	0.2969
Zahid	0.1406	0.5781	0.2969
Agrawal & Gonçalves	0.1094	0.4688	0.2500
Roman-Gomez	0.0938	0.5156	0.1563
<i>baseline</i>	0.0625	0.5313	0.1094

Early birds evaluation in reviews (NL)

Team	Gender
Roman-Gomez	0.6200
Waser*	0.6000
Gencheva <i>et al.</i>	0.5600
<i>baseline</i>	0.5600
Bayot & Gonçalves	0.5400
Bilan <i>et al.</i>	0.5400

Team	Gender
Dichiu & Rancea	0.5400
Garciarena <i>et al.</i>	0.5400
Zahid	0.5400
Kocher & Savoy	0.5200
Agrawal & Gonçalves	0.5000
Busger <i>et al.</i>	0.5000

Team	Gender
Devalkeneer	0.5000
Modaresi <i>et al.</i>	0.5000
Modaresi(a)	0.5000
Poongunran	0.4800
Bougiatiotis & Krithara	0.4400

Final evaluation in blogs (EN/ES)

English				Spanish			
Team	Joint	Gender	Age	Team	Joint	Gender	Age
Bougiatiotis & Krithara	0.3974	0.6923	0.5513	Busger <i>et al.</i>	0.4286	0.7143	0.5179
Busger <i>et al.</i>	0.3846	0.6410	0.5897	Modaresi <i>et al.</i>	0.4286	0.6964	0.5179
Modaresi <i>et al.</i>	0.3846	0.7564	0.5128	Bilan <i>et al.</i>	0.3750	0.6250	0.4643
Bilan <i>et al.</i>	0.3333	0.7436	0.4487	Markov <i>et al.</i>	0.3750	0.6607	0.4464
Waser*	0.3205	0.5897	0.4359	Dichiu & Rancea	0.3214	0.6429	0.4643
Devalkeneer	0.3205	0.6026	0.4487	Bayot & Gonçalves	0.3036	0.5893	0.4821
Modaresi(a)	0.3205	0.6667	0.4487	Modaresi(a)	0.3036	0.6964	0.4464
Markov <i>et al.</i>	0.2949	0.6154	0.4487	Devalkeneer	0.2857	0.5179	0.4821
Roman-Gomez	0.2821	0.6538	0.3974	Agrawal & Gonçalves	0.2857	0.5357	0.4821
Dichiu & Rancea	0.2692	0.6154	0.4103	Deneva	0.2679	0.7321	0.3214
Gencheva <i>et al.</i>	0.2564	0.6795	0.3718	Waser*	0.2679	0.5893	0.4107
Kocher & Savoy	0.2564	0.5769	0.4103	Bougiatiotis & Krithara	0.2500	0.6786	0.3214
Ashraf <i>et al.</i>	0.2564	0.5769	0.3718	Gencheva <i>et al.</i>	0.2500	0.6250	0.3214
Bayot & Gonçalves	0.2179	0.6282	0.3590	Garciarena <i>et al.</i>	0.2500	0.5000	0.4286
Deneva	0.2051	0.5128	0.3718	Zahid	0.2143	0.4821	0.4464
Bakkar <i>et al.</i>	0.2051	0.5385	0.3718	Kocher & Savoy	0.1964	0.5357	0.3393
Agrawal & Gonçalves	0.1923	0.5128	0.3846	Roman-Gomez	0.1250	0.5000	0.2500
Zahid	0.1923	0.5000	0.3846	<i>baseline</i>	0.1250	0.5000	0.1786
Aceituno	0.1667	0.5000	0.3205	Aceituno	0.0893	0.4643	0.2143
Garciarena <i>et al.</i>	0.1538	0.4615	0.3718				
Pimas <i>et al.</i>	0.1410	0.5769	0.3205				
<i>baseline</i>	0.0897	0.5641	0.1923				

Final evaluation in reviews (NL)

Team	Gender
Bayot & Gonçalves	0.5680
Roman-Gomez	0.5620
Bilan <i>et al.</i>	0.5500
Waser*	0.5320
<i>baseline</i>	0.5300
Dichiu & Rancea	0.5260
Garciarena <i>et al.</i>	0.5260

Team	Gender
Poongunran	0.5140
Gencheva <i>et al.</i>	0.5100
Markov <i>et al.</i>	0.5100
Agrawal & Gonçalves	0.5080
Devalkeneer	0.5060
Aceituno	0.5040
Kocher & Savoy	0.5040

Team	Gender
Modaresi <i>et al.</i>	0.5040
Busger <i>et al.</i>	0.5000
Modaresi(a)	0.5000
Deneva	0.4980
Bougiatiotis & Krithara	0.4160

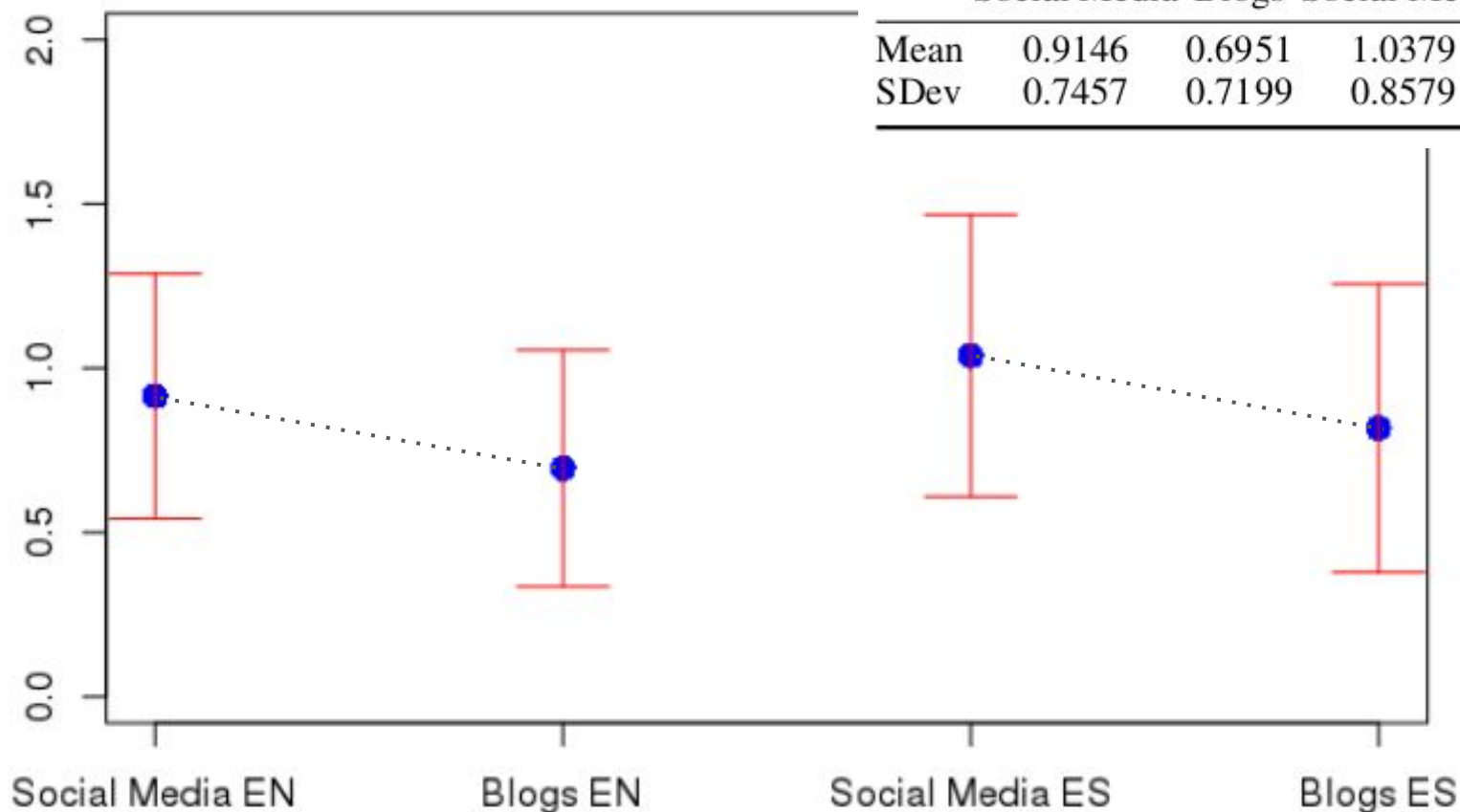
Social media vs. blogs in English

Team	Joint		Gender		Age	
	Social Media	Blogs	Social Media	Blogs	Social Media	Blogs
Agrawal & Gonçalves	0.1724	0.1923	0.5431	0.5128	0.3103	0.3846
Ashraf <i>et al.</i>	0.1494	0.2564	0.4971	0.5769	0.2902	0.3718
Bakkar <i>et al.</i>	0.1466	0.2051	0.5029	0.5385	0.2874	0.3718
Bilan <i>et al.</i>	0.1667	0.3333	0.5374	0.7436	0.2902	0.4487
Bougiatiotis & Krithara	0.1724	0.3974	0.5345	0.6923	0.3046	0.5513
Busger <i>et al.</i>	0.1897	0.3846	0.5575	0.6410	0.3046	0.5897
Devalkeneer	0.1839	0.3205	0.5259	0.6026	0.2931	0.4487
Dichiu & Rancea	0.1753	0.2692	0.5345	0.6154	0.2989	0.4103
Garciarena <i>et al.</i>	0.1609	0.1538	0.5201	0.4615	0.2816	0.3718
Gencheva <i>et al.</i>	0.1638	0.2564	0.5287	0.6795	0.2902	0.3718
Kocher & Savoy	0.1552	0.2564	0.5144	0.5769	0.2816	0.4103
Modaresi(a)	0.1724	0.3205	0.5057	0.6667	0.3218	0.4487
Modaresi <i>et al.</i>	0.1552	0.3846	0.5029	0.7564	0.3017	0.5128
Pimas <i>et al.</i>	0.0057	0.1410	0.0201	0.5769	0.0086	0.3205
Roman-Gomez	0.1494	0.2821	0.5144	0.6538	0.2874	0.3974
Waser*	0.2098	0.3205	0.5230	0.5897	0.3879	0.4359
Zahid	0.1523	0.1923	0.4885	0.5000	0.3103	0.3846
Min	0.0057	0.1410	0.0201	0.4615	0.0086	0.3205
Q1	0.1523	0.2051	0.5029	0.5769	0.2874	0.3718
Median	0.1638	0.2692	0.5201	0.6026	0.2931	0.4103
Mean	0.1577	0.2745	0.4912	0.6109	0.2853	0.4253
SDev	0.0425	0.0794	0.1227	0.0827	0.0754	0.0704
Q3	0.1724	0.3205	0.5345	0.6667	0.3046	0.4487
Max	0.2098	0.3974	0.5575	0.7564	0.3879	0.5897

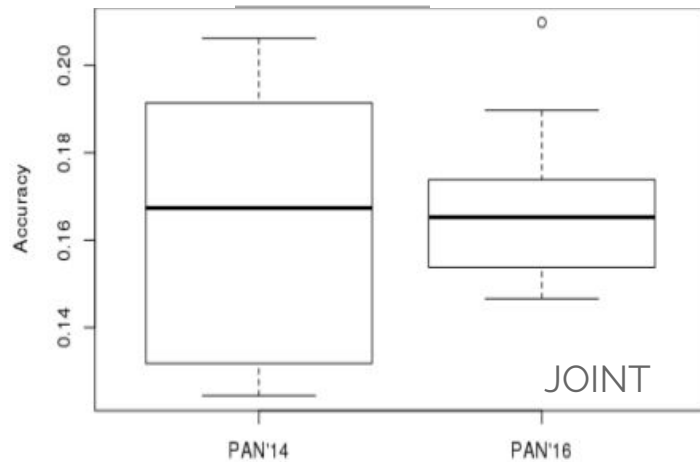
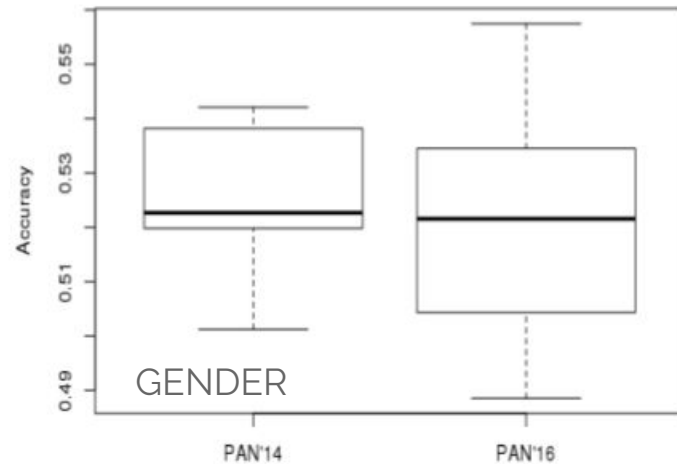
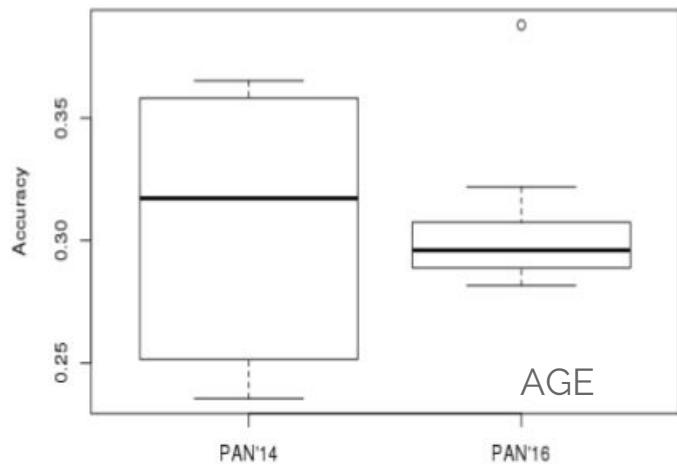
Social media vs. blogs in Spanish

Team	Joint		Gender		Age	
	Social Media	Blogs	Social Media	Blogs	Social Media	Blogs
Agrawal & Gonçalves	0.1094	0.2857	0.4688	0.5357	0.2500	0.4821
Bilan <i>et al.</i>	0.1406	0.3750	0.5781	0.6250	0.2969	0.4643
Bougiatiotis & Krithara	0.2031	0.2500	0.5781	0.6786	0.3438	0.3214
Busger <i>et al.</i>	0.1875	0.4286	0.5313	0.7143	0.2813	0.5179
Devalkeneer	0.1875	0.2857	0.5625	0.5179	0.3594	0.4821
Dichiu & Rancea	0.1719	0.3214	0.5469	0.6429	0.2813	0.4643
Garciarena <i>et al.</i>	0.1875	0.2500	0.5625	0.5000	0.2969	0.4286
Gencheva <i>et al.</i>	0.1563	0.2500	0.6250	0.6250	0.2656	0.3214
Kocher & Savoy	0.2031	0.1964	0.5000	0.5357	0.3125	0.3393
Modaresi(a)	0.1406	0.3036	0.6250	0.6964	0.2969	0.4464
Modaresi <i>et al.</i>	0.2031	0.4286	0.6406	0.6964	0.2813	0.5179
Roman-Gomez	0.0938	0.1250	0.5156	0.5000	0.1563	0.2500
Waser*	0.1875	0.2679	0.7031	0.5893	0.2813	0.4107
Zahid	0.1406	0.2143	0.5781	0.4821	0.2969	0.4464
Min	0.0938	0.1250	0.4688	0.4821	0.1563	0.2500
Q1	0.1406	0.2500	0.5352	0.5224	0.2813	0.3572
Median	0.1797	0.2768	0.5703	0.6072	0.2891	0.4464
Mean	0.1652	0.2844	0.5725	0.5957	0.2857	0.4209
SDev	0.0356	0.0848	0.0615	0.0831	0.0468	0.0819
Q3	0.1875	0.3170	0.6133	0.6697	0.2969	0.4776
Max	0.2031	0.4286	0.7031	0.7143	0.3594	0.5179

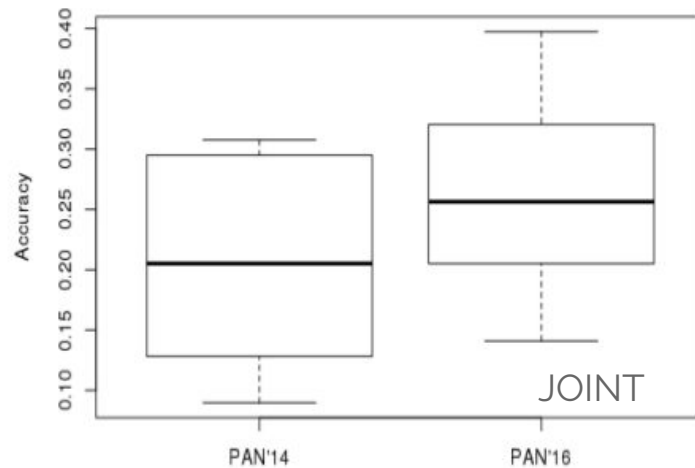
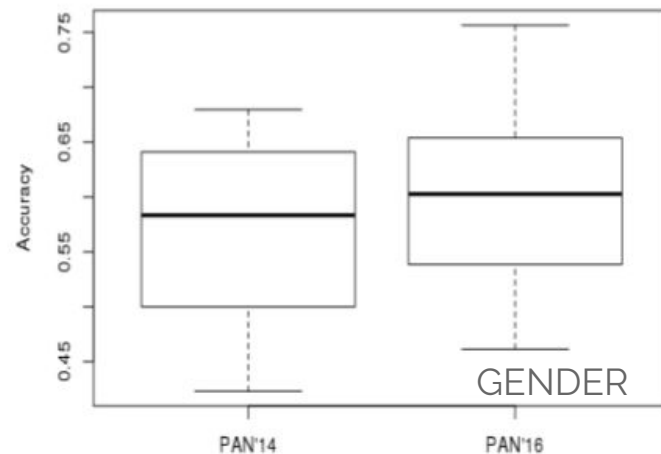
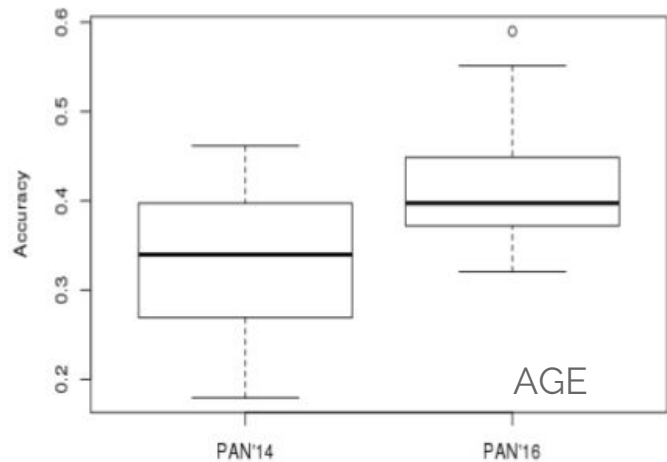
Distances in age identification



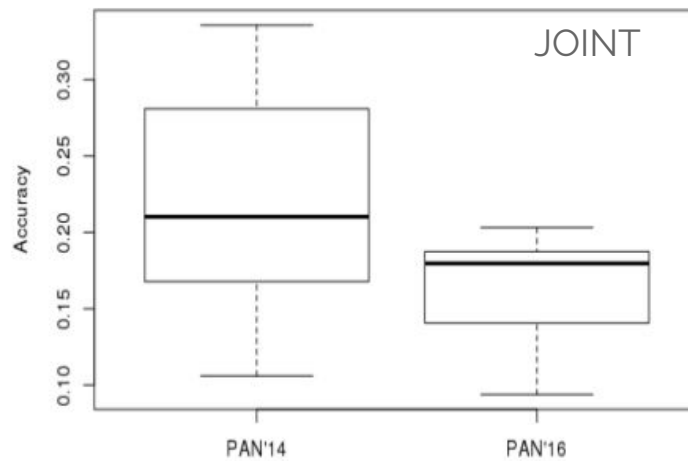
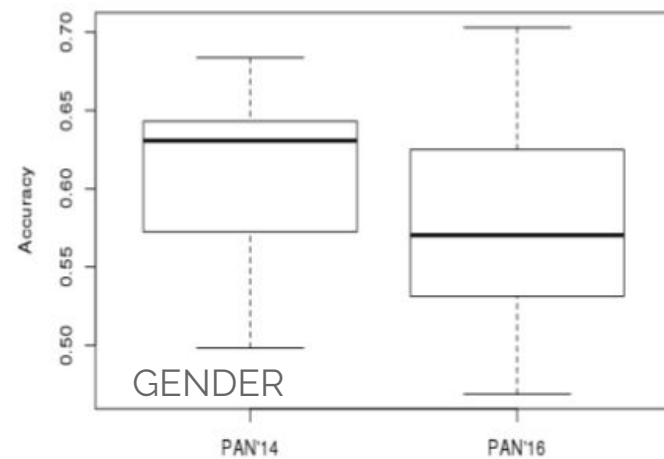
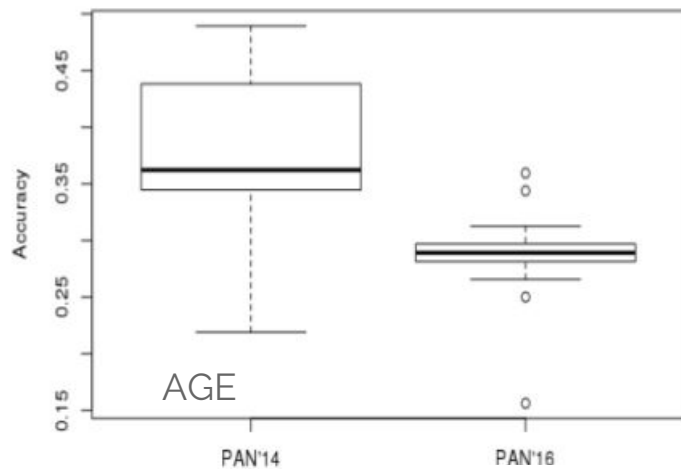
2014 vs. 2016 in social media (English)



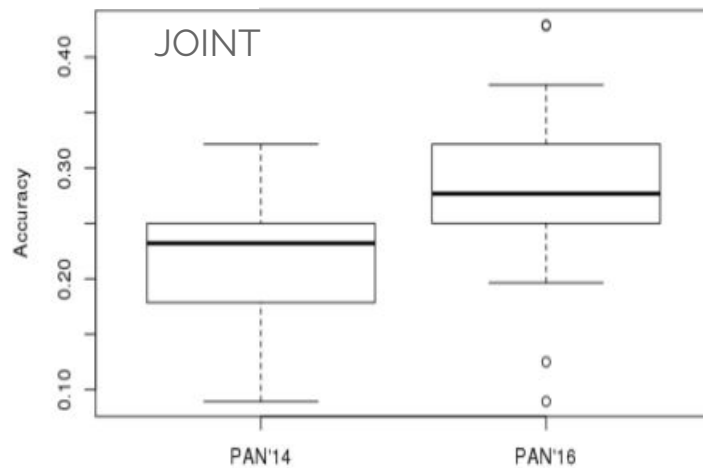
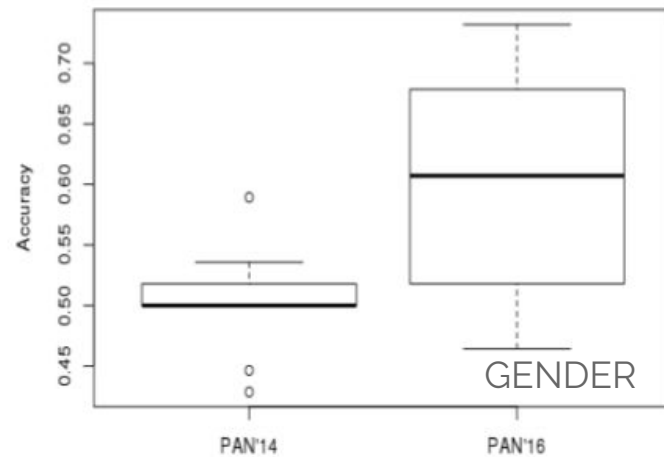
2014 vs. 2016 in blogs (English)



2014 vs. 2016 in social media (Spanish)



2014 vs. 2016 in blogs (Spanish)



Final ranking

$$\overline{gender} = \frac{gender_en + gender_es + gender_nl}{3}$$

$$\overline{age} = \frac{age_en + age_es}{2}$$

$$\overline{joint} = \frac{joint_en + joint_es}{2}$$



$$ranking = \frac{\overline{gender} + \overline{age} + \overline{joint}}{3}$$

Ranking	Team	Global	English	Spanish	Dutch
1	Busger <i>et al.</i>	0.5263	0.3846	0.4286	0.5000
2	Modaresi <i>et al.</i>	0.4934	0.3205	0.4286	0.5040
3	Bilan <i>et al.</i>	0.4834	0.3333	0.3750	0.5500
4	Modaresi(a)	0.4602	0.3205	0.3036	0.5000
5	Markov <i>et al.</i>	0.4593	0.2949	0.3750	0.5100
6	Bougiatiotis & Krithara	0.4519	0.3974	0.2500	0.4160
7	Dichiu & Rancea	0.4425	0.2692	0.3214	0.5260
8	Devalkeneer	0.4387	0.3205	0.2968	0.5060
9	Waser*	0.4293	0.3205	0.2679	0.5320
10	Bayot & Gonçalves	0.4255	0.2179	0.3036	0.5680
11	Gencheva <i>et al.</i>	0.4015	0.2564	0.2500	0.5100
12	Agrawal & Gonçalves	0.3971	0.1923	0.2857	0.5080
13	Deneva	0.3880	0.2051	0.2679	0.4980
14	Kocher & Savoy	0.3800	0.2564	0.1964	0.5040
15	Roman-Gomez	0.3664	0.2821	0.1250	0.5620
16	Garciarena <i>et al.</i>	0.3660	0.1538	0.2500	0.5260
17	Zahid	0.3154	0.1923	0.2143	-
18	Aceituno	0.2949	0.1667	0.0893	0.5040
19	Poongunran	0.1793	-	-	0.5140
20	Ashraf <i>et al.</i>	0.1688	0.2564	-	-
21	Bakkar <i>et al.</i>	0.1560	0.2051	-	-
22	Pimas <i>et al.</i>	0.1410	0.1410	-	-

PAN-AP 2016 best results

Age and Gender			
Language	<i>Joint</i>	Gender	Age
English	0.3974	0.7564	0.5897
Spanish	0.4286	0.7321	0.5179
Dutch	-	0.5680	-

Conclusions

- High combination of features: stylometric, n-grams, POS, collocations... First positions with:
 - Second order representation
 - Word2vec
- Early birds (social media in English and Spanish; reviews in Dutch):
 - Higher results for gender identification in Spanish than in English.
 - In Dutch and English most participants below baseline.
- Final evaluation (blogs in English and Spanish; reviews in Dutch):
 - Similar results for English and Spanish.
 - Most Dutch results below baseline.
- The effect of the cross-genre evaluation is higher in social media than in blogs:
 - Results in blogs are higher than in social media, except in case of gender identification in Spanish.
 - Distances in age identification are lower in blogs than in social media.
- Comparative results between 2014 and 2015 suggests:
 - There is no strong effect in the cross-genre evaluation in social media in English.
 - There is a strong impact in Spanish social media, specially in joint and age identification.
 - In blogs the effect is positive on age and joint identification in English and gender and joint in Spanish.
- Depending on the genre, the cross-genre may have a positive effect:
 - Learning from Twitter: spontaneous, without censorship, high number of tweets per user.
 - Evaluating on Blogs: difficult to obtain good labeled data.

Task impact

	PARTICIPANTS	COUNTRIES	CITATIONS
PAN-AP 2013	21	16	67 (+28)
PAN-AP 2014	10	8	41 (+25)
PAN-AP 2015	22	13	42 (+25)
PAN-AP 2016	22	15	5

Industry at PAN (Author Profiling)

Organisation



Sponsors



Participants



Next year?





On behalf of the author profiling task organisers:

Thank you very much for participating
and hope to see you next year!!