



6th Author Profiling task at PAN Multimodal Gender Identification in Twitter

PAN-AP-2018 CLEF 2018
Avignon, 10-14 September

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Introduction

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

This is crucial for:

- Marketing.
- Security.
- Forensics.



Task goal

To investigate the identification of author's **gender** with multimodal information: texts + images.

Three languages:

Arabic

English

Spanish

Corpus

- PAN-AP'17 subset extended with images shared in author's timelines:
 - 100 tweets per author.
 - 10 images per author.

	(AR) Arabic	(EN) English	(ES) Spanish	Total
Training	1,500	3,000	3,000	7,500
Test	1,000	1,900	2,200	5,100
Total	2,500	4,900	5,200	12,600

Evaluation measures

The **accuracy** is calculated per *modality* and language:

- Text-based.
- Image-based.
- Combined.

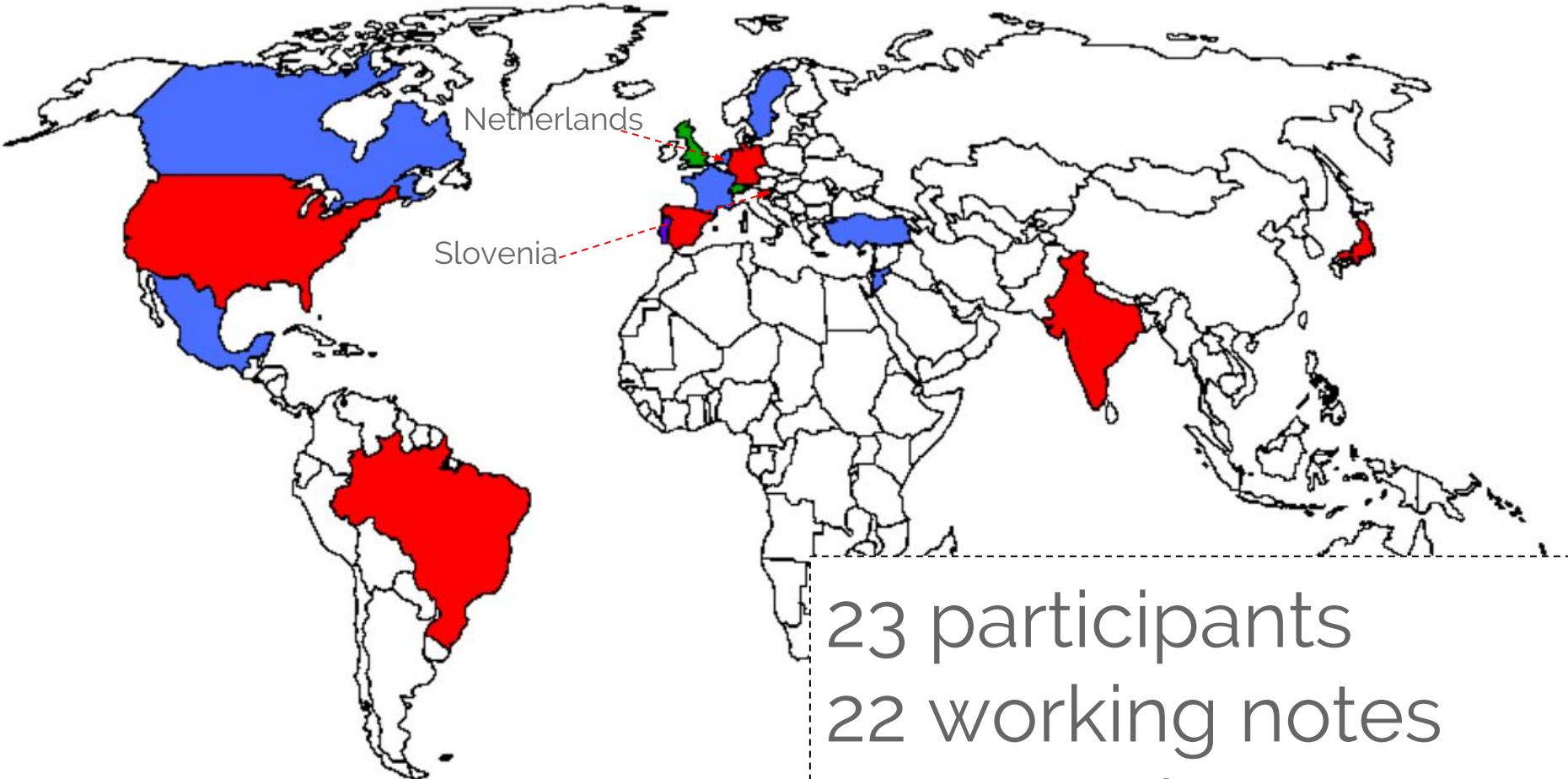
The final ranking is the average of the combined* accuracies per language:

$$\text{ranking} = \frac{acc_{ar} + acc_{en} + acc_{es}}{3}$$

* If only the textual approach was submitted, its accuracy has been used

Baselines

- **BASELINE-stat:** A statistical baseline that emulates random choice. Both modalities.
- **BASELINE-bow:**
 - Documents represented as bag-of-words.
 - The 5,000 most common words in the training set.
 - Weighted by absolute frequency.
 - Preprocess: lowercase, removal of punctuation signs and numbers, removal of stopwords.
 - Textual modality.
- **BASELINE-rgb:**
 - RGB color for each pixel in each author images.
 - The author is represented with the minimum, maximum, mean, median, and standard deviation of the RGB values.
 - Images modality.



23 participants
22 working notes
17 countries

Approaches

What kind of ...

Preprocessing

Features

Methods

... did the teams perform?

Approaches - Preprocessing

TEXTS	Punctuation signs	Ciccone <i>et al.</i> , Stout <i>et al.</i> , HaCohen-Kerner <i>et al.</i> , Veenhoven <i>et al.</i>
	Character flooding	Ciccone <i>et al.</i> , Raiyani <i>et al.</i>
	Lowercase	Von Däniken <i>et al.</i> , Veenhoven <i>et al.</i> , Nieuwenhuis <i>et al.</i> , Bayot & Gonçalves, Kosse <i>et al.</i> , Stout <i>et al.</i> , Schaetti, HaCohen-Kerner <i>et al.</i>
	Stopwords	Ciccone <i>et al.</i> , Raiyani <i>et al.</i> , HaCohen-Kerner <i>et al.</i> , Veenhoven <i>et al.</i>
	Twitter specific components: hashtags, urls, mentions and RTs	Ciccone <i>et al.</i> , Takahashi <i>et al.</i> , Stout <i>et al.</i> , Raiyani <i>et al.</i> , Schaetti, HaCohen-Kerner <i>et al.</i> , Von Däniken <i>et al.</i> , Martinc <i>et al.</i> , Veenhoven <i>et al.</i> , Nieuwenhuis <i>et al.</i> , Kosse <i>et al.</i>
	Contractions and abbreviations	Stout <i>et al.</i> , Raiyani <i>et al.</i>
	Normalisation and diacritics removal in Arabic	Ciccone <i>et al.</i>
	Resizing, rescaling	Takahashi <i>et al.</i> , Martinc <i>et al.</i> , Sierra-Loaiza & González
	Normalisation (subtracting the average RGB value per lang)	Takahashi <i>et al.</i>

Approaches - Textual Features

Stylistic features: <ul style="list-style-type: none">- Ratios of links- Hashtag or user mentions- Character flooding- Emoticons / laughter expressions- Domain names	Patra <i>et al.</i> , Karlgren <i>et al.</i> , HaCohen-Kerner <i>et al.</i> , Von Däniken <i>et al.</i>
N-gram models	Stout <i>et al.</i> , Sandroni-Dias & Paraboni, López-Santillán <i>et al.</i> , Von Däniken <i>et al.</i> , Tellez <i>et al.</i> , Nieuwenhuis <i>et al.</i> , Kosse <i>et al.</i> , Daneshvar, HaCohen-Kerner <i>et al.</i> , Ciccone <i>et al.</i> , Aragón & López
LSA	Patra <i>et al.</i>
Second order representation	Áragon & López
A variation of LDSE	Gàrigo-Orts
Word embeddings	Martinc <i>et al.</i> , Veenhoven <i>et al.</i> , Bayot & Gonçalves, López-Santillán <i>et al.</i> , Takahashi <i>et al.</i> , Patra <i>et al.</i>
Character embeddings	Schaetti

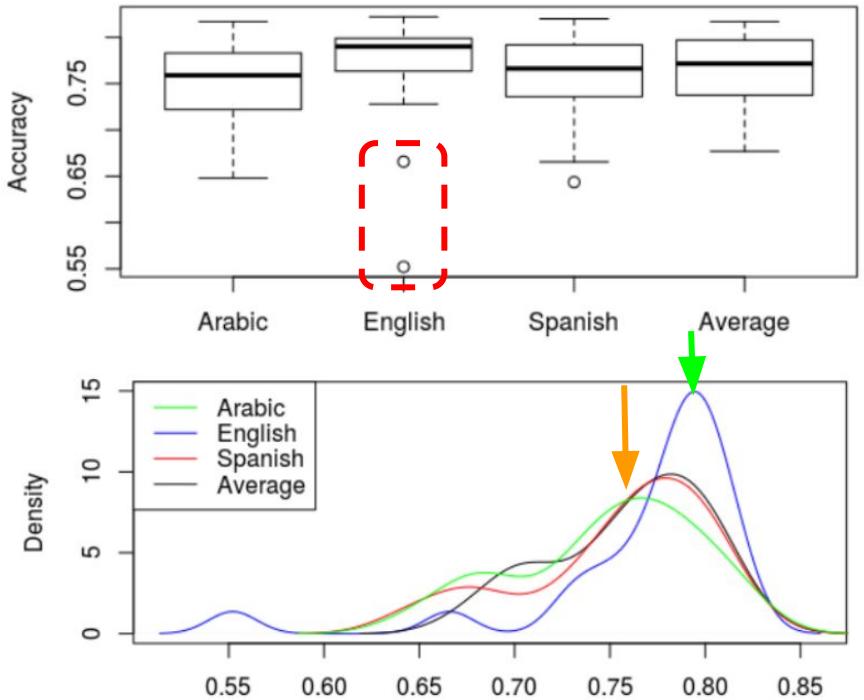
Approaches - Image Features

Face detection	Stout <i>et al.</i> , Ciccone <i>et al.</i> , Veenhoven <i>et al.</i>
Objects detection	Ciccone <i>et al.</i>
Local binary patterns	Ciccone <i>et al.</i>
Hand-crafted features	HaCohen-Kerner <i>et al.</i>
Color histogram	Ciccone <i>et al.</i> , HaCohen-Kerner <i>et al.</i>
Bag of Visual Words	Tellez <i>et al.</i>
Image resources and tools (e.g. ImageNet, TorchVision...)	Patra <i>et al.</i> , Nieuwenhuis <i>et al.</i> , Aragón & López, Schaetti, Takahashi <i>et al.</i>

Approaches - Methods

Logistic regression	Sandroni-Dias & Paraboni, HaCohen-Kerner <i>et al.</i> , Von Däniken <i>et al.</i> , Nieuwenhuis <i>et al.</i>
SVM	López-Santillán <i>et al.</i> , Aragón & López, Ciccone <i>et al.</i> , Patra <i>et al.</i> , Tellez <i>et al.</i> , Veenhoven <i>et al.</i>
Multilayer Perceptron	HaCohen-Kerner <i>et al.</i>
Basic feed-forward network	Kosse <i>et al.</i>
Distance-based method	Tellez <i>et al.</i> , Karlgren <i>et al.</i>
IF condition	Gáribo-Orts
RNN	Takahashi <i>et al.</i> , Bayot & Gonçalves, Stout <i>et al.</i>
CNN	Schaetti
ResNet18	Schaetti
Bi-LSTM	Veenhoven <i>et al.</i>

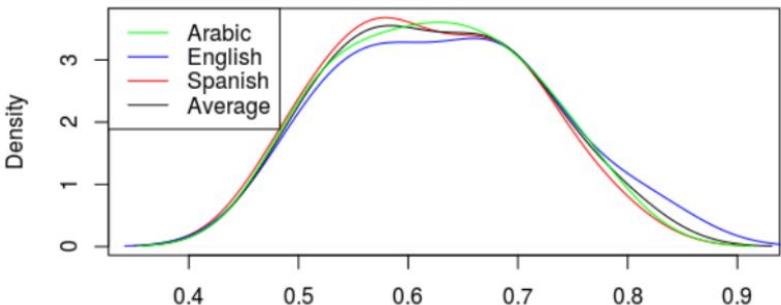
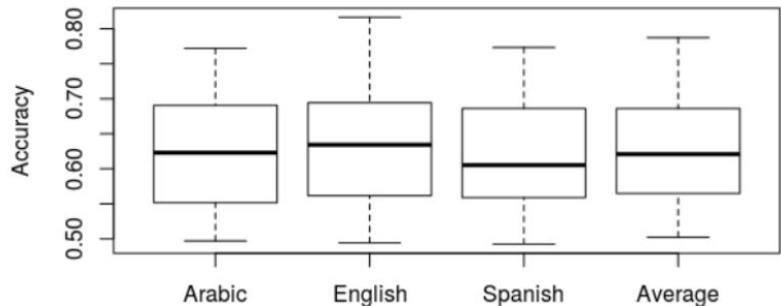
Textual modality



Ranking	Team	Arabic	English	Spanish	Average
1	Daneshvar	0.8090	0.8221	0.8200	0.8170
2	Tellez <i>et al.</i>	0.8170	0.8121	0.8005	0.8099
3	Nieuwenhuis & Wilkens	0.7830	0.8116	0.8027	0.7991
4	Sierra-Loaiza & González	0.8120	0.8011	0.7827	0.7986
5	Ciccone <i>et al.</i>	0.7910	0.8074	0.7959	0.7981
6	Kosse <i>et al.</i>	0.7920	0.8074	0.7918	0.7971
7	Takahashi <i>et al.</i>	0.7710	0.7968	0.7864	0.7847
8	Veenhoven <i>et al.</i>	0.7490	0.7926	0.8036	0.7817
9	Martinc <i>et al</i>	0.7760	0.7900	0.7782	0.7814
10	López-Santillán <i>et al.</i>	0.7760	0.7847	0.7677	0.7761
11	Hacohen-Kerner <i>et al.</i> (B)	0.7590	0.7911	0.7650	0.7717
12	Hacohen-Kerner <i>et al.</i> (A)	0.7590	0.7911	0.7650	0.7717
13	Stout <i>et al.</i>	0.7600	0.7853	0.7405	0.7619
14	Gopal-Patra <i>et al.</i>	0.7430	0.7558	0.7586	0.7525
15	von Däniken <i>et al.</i>	0.7320	0.7742	0.7464	0.7509
16	Schaetti baseline-bow	0.7390	0.7711	0.7359	0.7487
17	Aragon & Lopez	0.6480	0.7963	0.7686	0.7376
18	Bayot & Gonçalves	0.6760	0.7716	0.6873	0.7116
19	Garibo	0.6750	0.7363	0.7164	0.7092
20	Sezerer <i>et al.</i>	0.6920	0.7495	0.6655	0.7023
21	Raiyani <i>et al.</i>	0.7220	0.7279	0.6436	0.6978
22	Sandroni-Dias & Paraboni baseline-stats	0.6870	0.6658	0.6782	0.6770
23	Karlgren <i>et al.</i>	0.5000	0.5000	0.5000	0.5000
		-	0.5521	-	-

- AR: n-grams
- EN: n-grams
- ES: n-grams

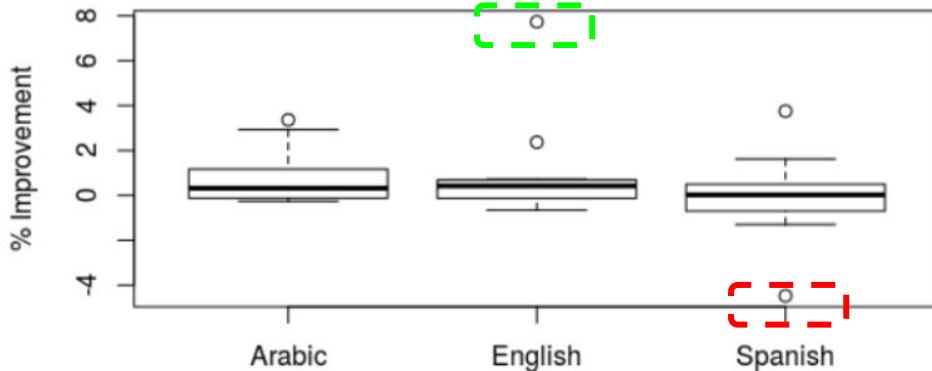
Images modality



Ranking	Team	Arabic	English	Spanish	Average
1	Takahashi <i>et al.</i>	0.7720	0.8163	0.7732	0.7872
2	Sierra-Loaiza & González	0.7280	0.7442	0.7100	0.7274
3	Ciccone <i>et al.</i>	0.7010	0.6963	0.6805	0.6926
4	Aragon & Lopez	0.6800	0.6921	0.6668	0.6796
5	Gopal-Patra <i>et al.</i>	0.6570	0.6747	0.6918	0.6745
6	Stout <i>et al.</i>	0.6230	0.6584	0.6232	0.6349
7	Nieuwenhuis & Wilkens	0.6230	0.6100	0.5873	0.6068
8	Tellez <i>et al.</i>	0.5900	0.5468	0.5691	0.5686
9	Schaetti	0.5430	0.5763	0.5782	0.5658
10	Martinc <i>et al.</i>	0.5600	0.5826	0.5486	0.5637
	baseline-rgb	0.5410	0.5179	0.5191	0.5260
11	Hacohen-Kerner <i>et al.</i> (B)	0.5100	0.4942	0.5027	0.5023
12	Hacohen-Kerner <i>et al.</i> (A)	0.4970	0.5174	0.4923	0.5022
	baseline-stats	0.5000	0.5000	0.5000	0.5000

- **Best:** Pre-trained CNN w. ImageNet
- **2nd. AR:** VGG16 + ResNet50 from ImageNet
- **2nd. EN:** VGG16 + ResNet50 from ImageNet
- **2nd. ES:** Color histogram + faces + objects + local binary patterns

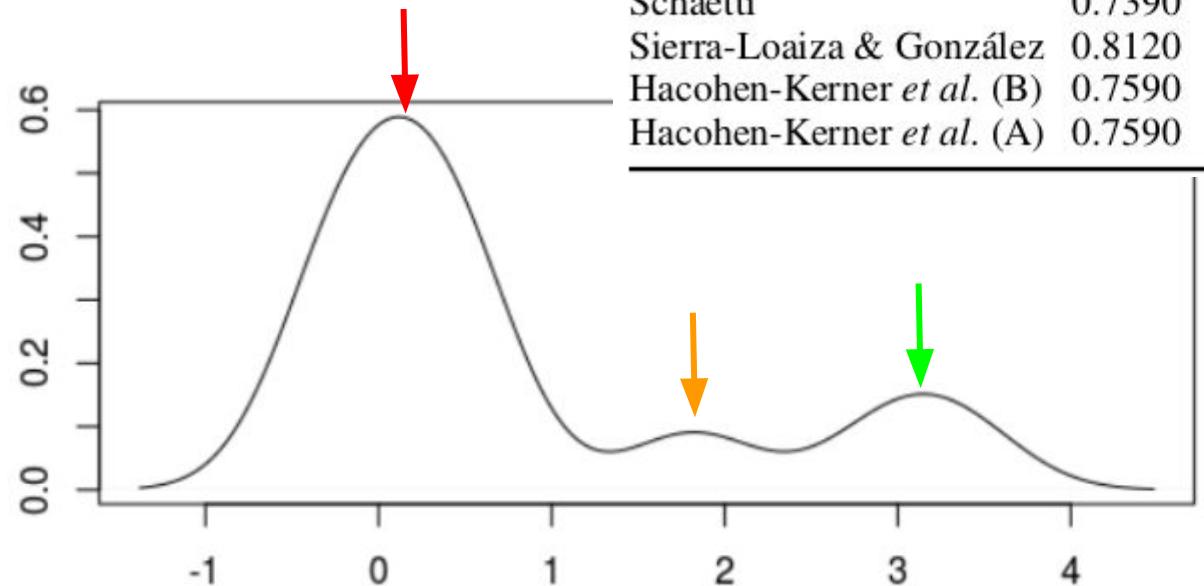
Improvement with images



	Arabic	English	Spanish
Min	-0.2635	-0.6526	-4.4717
Q1	-0.0616	-0.0647	-0.6613
Median	0.3185	0.4249	0.0257
Mean	0.7613	1.0102	-0.0609
SDev	1.2513	2.2473	1.9087
Q3	0.8487	0.6788	0.4898
Max	3.3647	7.7309	3.7513
Skewness	1.2095	2.4716	-0.3778
Kurtosis	2.9616	8.0027	4.4883
Normality (p-value)	0.0010	0.0000	0.1316

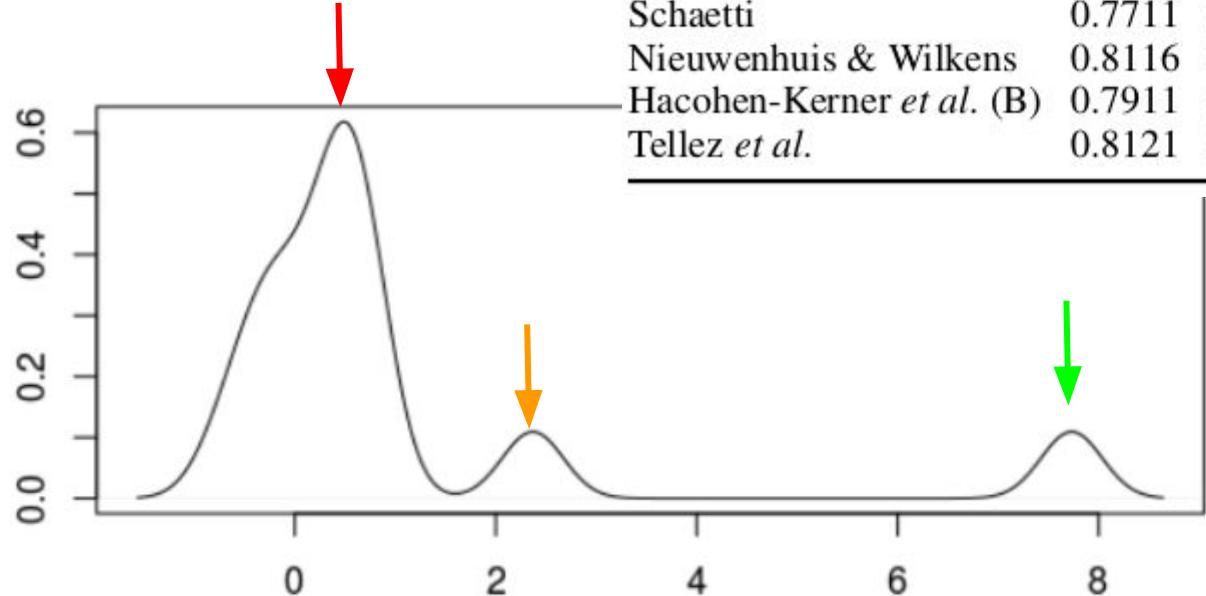
- In average, there is almost no improvement.
- Some systems obtain high improvements (up to 7.73%)
 - Pre-trained CNN w. ImageNet.

Improvement (AR)

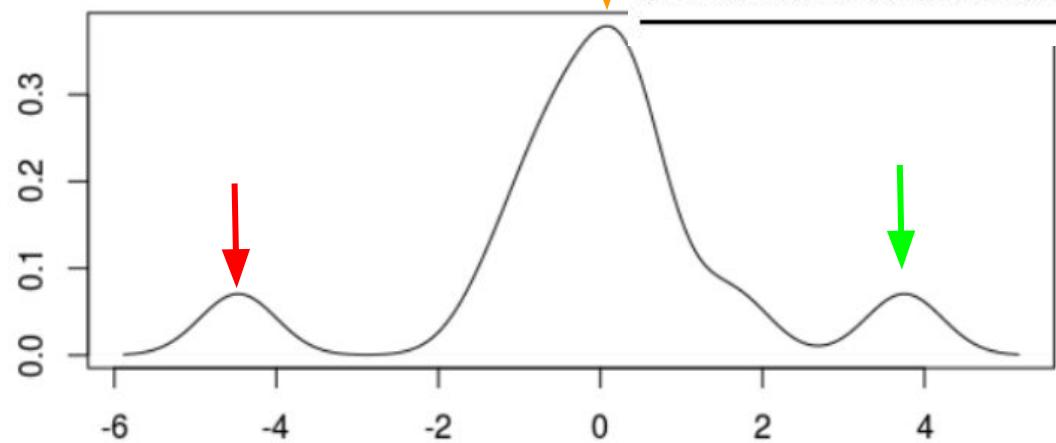


Team	Texts	Images	Combined	Improvement
Gopal-Patra <i>et al.</i>	0.7430	0.6570	0.7680	3.3647%
Aragon & Lopez	0.6480	0.6800	0.6670	2.9321%
Takahashi <i>et al.</i>	0.7710	0.7720	0.7850	1.8158%
Stout <i>et al.</i>	0.7600	0.6230	0.7640	0.5263%
Nieuwenhuis & Wilkens	0.7830	0.6230	0.7870	0.5109%
Ciccone <i>et al.</i>	0.7910	0.7010	0.7940	0.3793%
Martinc <i>et al</i>	0.7760	0.5600	0.7780	0.2577%
Tellez <i>et al.</i>	0.8170	0.5900	0.8180	0.1224%
Schaetti	0.7390	0.5430	0.7390	0.0000%
Sierra-Loaiza & González	0.8120	0.7280	0.8100	-0.2463%
Hacohen-Kerner <i>et al.</i> (B)	0.7590	0.5100	0.7570	-0.2635%
Hacohen-Kerner <i>et al.</i> (A)	0.7590	0.4970	0.7570	-0.2635%

Improvement (EN)

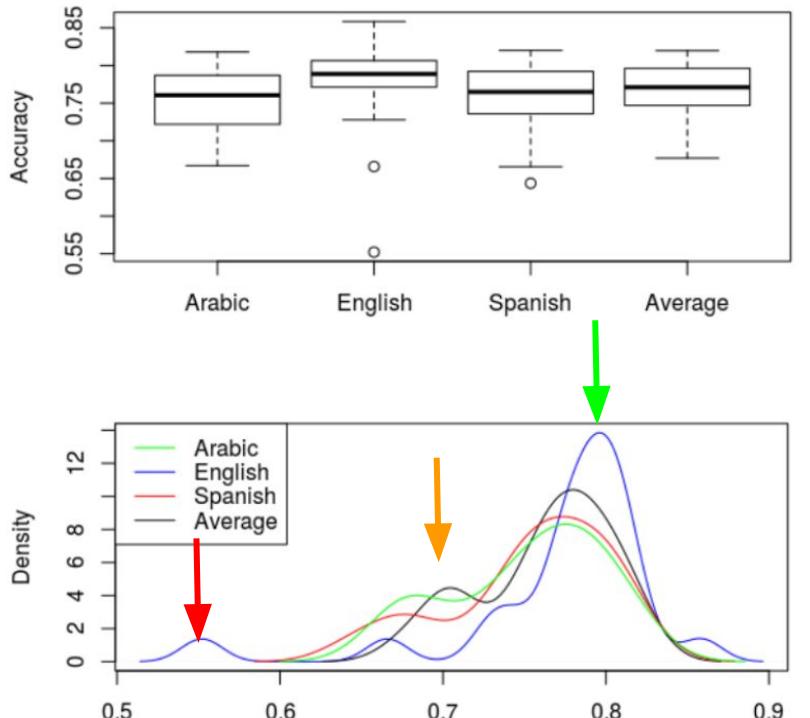


Improvement (ES)



Team	Texts	Images	Combined	Improvement
Takahashi <i>et al.</i>	0.7864	0.7732	0.8159	3.7513
Gopal-Patra <i>et al.</i>	0.7586	0.6918	0.7709	1.6214
Ciccone <i>et al.</i>	0.7959	0.6805	0.8000	0.5151
Aragon & Lopez	0.7686	0.6668	0.7723	0.4814
Stout <i>et al.</i>	0.7405	0.6232	0.7432	0.3646
Martinc <i>et al.</i>	0.7782	0.5486	0.7786	0.0514
Schaetti	0.7359	0.5782	0.7359	0.0000
Hacohen-Kerner <i>et al.</i> (A)	0.7650	0.4923	0.7623	-0.3529
Tellez <i>et al.</i>	0.8005	0.5691	0.7955	-0.6246
Hacohen-Kerner <i>et al.</i> (B)	0.7650	0.5027	0.7591	-0.7712
Nieuwenhuis & Wilkens	0.8027	0.5873	0.7923	-1.2956
Sierra-Loaiza & González	0.7827	0.7100	0.7477	-4.4717

Final ranking



Ranking	Team	Arabic	English	Spanish	Average
1	Takahashi <i>et al.</i>	0.7850	0.8584	0.8159	0.8198
2	Daneshvar	0.8090	0.8221	0.8200	0.8170
3	Tellez <i>et al.</i>	0.8180	0.8068	0.7955	0.8068
4	Ciccone <i>et al.</i>	0.7940	0.8132	0.8000	0.8024
5	Kosse <i>et al.</i>	0.7920	0.8074	0.7918	0.7971
6	Nieuwenhuis & Wilkens	0.7870	0.8095	0.7923	0.7963
7	Sierra-Loaiza & González	0.8100	0.8063	0.7477	0.7880
8	Martinc <i>et al.</i>	0.7780	0.7926	0.7786	0.7831
9	Veenhoven <i>et al.</i>	0.7490	0.7926	0.8036	0.7817
10	López-Santillán <i>et al.</i>	0.7760	0.7847	0.7677	0.7761
11	Hacohen-Kerner <i>et al.</i> (A)	0.7570	0.7947	0.7623	0.7713
12	Gopal-Patra <i>et al.</i>	0.7680	0.7737	0.7709	0.7709
13	Hacohen-Kerner <i>et al.</i> (B)	0.7570	0.7889	0.7591	0.7683
14	Stout <i>et al.</i>	0.7640	0.7884	0.7432	0.7652
15	von Däniken <i>et al.</i>	0.7320	0.7742	0.7464	0.7509
16	Schaetti	0.7390	0.7711	0.7359	0.7487
17	Aragon & Lopez	0.6670	0.8016	0.7723	0.7470
18	Bayot & Gonçalves	0.6760	0.7716	0.6873	0.7116
19	Garibo	0.6750	0.7363	0.7164	0.7092
20	Sezerer <i>et al.</i>	0.6920	0.7495	0.6655	0.7023
21	Raiyani <i>et al.</i>	0.7220	0.7279	0.6436	0.6978
22	Sandroni-Dias & Paraboni	0.6870	0.6658	0.6782	0.6770
23	Karlgren <i>et al.</i>	-	0.5521	-	-

PAN-AP 2018 best results

Language	Textual	Images	Combined
Arabic	0.8170	0.7720	0.8180
English	0.8221	0.8163	0.8584
Spanish	0.8200	0.7732	0.8200

Conclusions

- Several approaches to tackle the task:
 - Deep learning prevailing.
- Textual classification:
 - Best results regarding textual subtask: n-grams + traditional methods (SVM, logistic reg.).
 - The second best result for Spanish: bi-LSTM with word embeddings.
- Images classification approaches based on:
 - Face recognition. <- Failed!
 - Pre-trained models and image processing tools such as ImageNet. <- Best results obtained with semantic features extracted from the images.
 - Hand-crafted features such as color histograms and bag-of-visual-words.
- Texts vs. Images:
 - Textual features discriminate better than images.
 - On average, there is no improvement when images are used.
 - Elaborated representations improves up to 7.73% (English).
- Best results:
 - Over 80% on average (EN 85.84%; ES 82%; AR: 81.80%).
 - English (85.84%): Takahashi et al. with deep learning techniques (RNN for text, ImageNet + CNN for images).
 - Spanish (82%): Daneshvar with SVM and combinations of n-grams (only textual features).
 - Arabic (81.80%): Tellez et al. with SVM + n-grams, and Bag of Visual Words.
- Insight:
 - Traditional approaches still remain competitive, but deep learning is acquiring strength.

Task impact

	PARTICIPANTS	COUNTRIES
PAN-AP 2013	21	16
PAN-AP 2014	10	8
PAN-AP 2015	22	13
PAN-AP 2016	22	15
PAN-AP 2017	22	19
PAN-AP 2018	23	17

Industry at PAN (Author Profiling)

Organisation



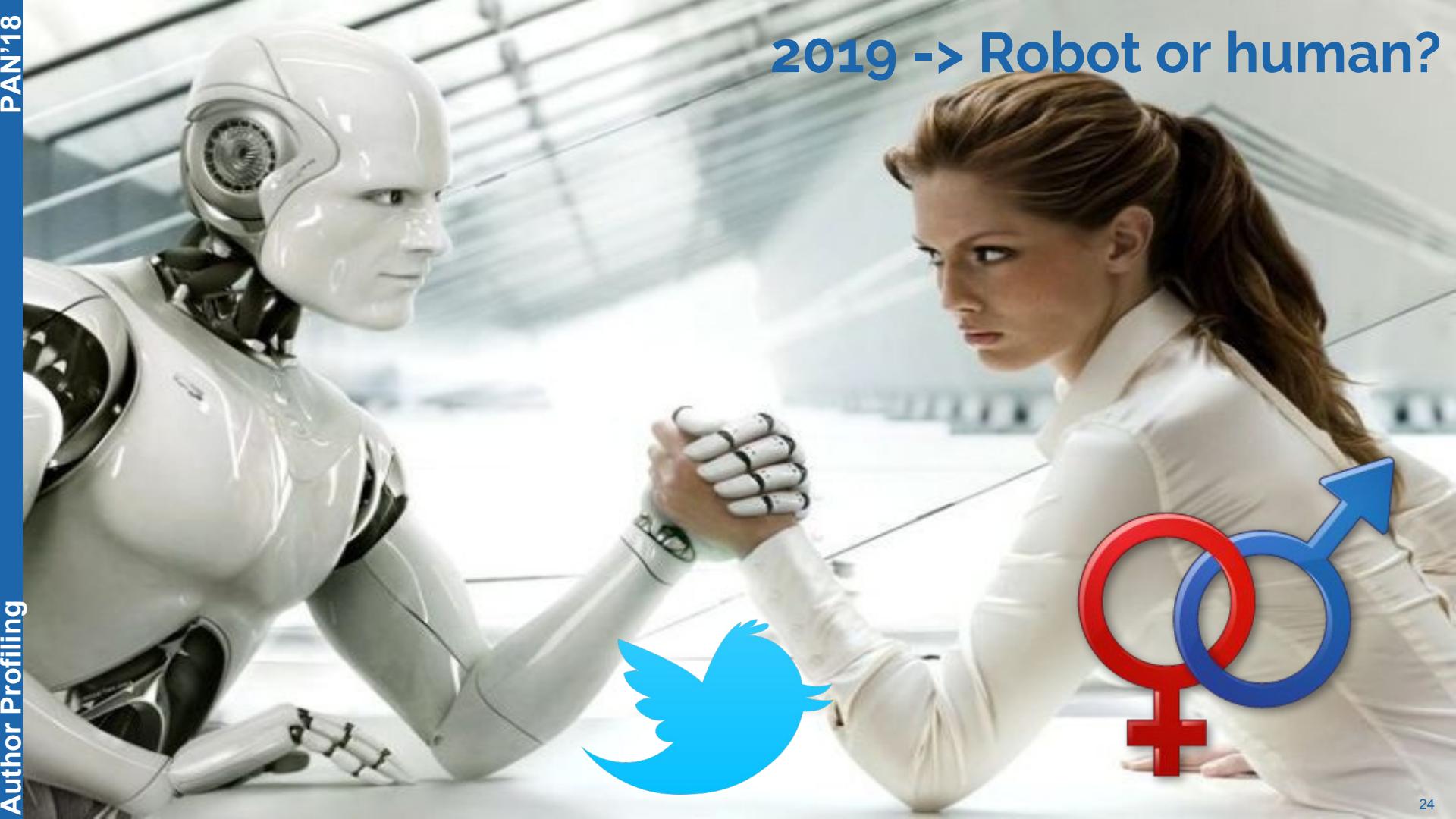
Participants



Sponsors



2019 -> Robot or human?





On behalf of the author profiling task organisers:

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