PAN @ CLEF 2019 - CELEBRITY PROFILING

CELEBRITY PROFILING ON TWITTER USING SOCIOLINGUISTIC FEATURES

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Summary

Social networks have been a revolutionary scenario for celebrities because they allow them to reach a wider audience with much higher frequency than using traditional means. These platforms enable them to improve or sometimes deteriorate, their careers through the construction of closer relationships with their fans and the acquisition of new ones. Indeed, networks have promoted the emergence of a new type of celebrities that exists only in the digital world.

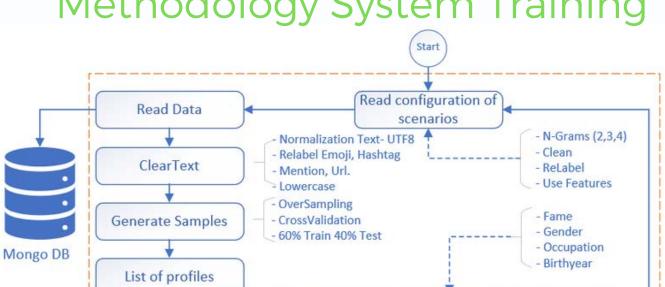
Being able to characterize the celebrities that are more active on social networks, such as Twitter, gives an enormous opportunity to identify what is their real level of fame, what is their relevance for an age group, or a specific gender or occupation. These facts may enrich decision making, especially in advertising and marketing.

Hypothesis - HO

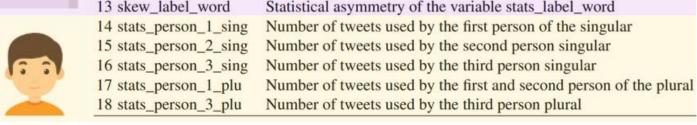
Profession	The profession is mainly associated with the use of "specialized" vocabulary. Therefore, the classification process must be based on the vocabulary collected by each profession.		
Gender	In gender, we want to establish features for the use of emojis, hashtags, men- tions, RT and URLs. For this, it is expected that the features associated with the words added to those found in the user profiles will improve the classifications.		
Fame Wo Ference C Bari Wo John Wa	Fame is perhaps the most important label in establishing features such as the use of emojis, hashtags, mentions, RT and URL. In addition, it is verified if the message is written in first, second or third person. With the above, it is expected that the features associated with the words added to those found in the usage profiles will improve the classifications.		
Birth years	This label is perhaps the most difficult to classify because the wide range of years from 1940 to 2011. For this reason, groups were established in order to generate features of use of emojis, hashtags, mentions, RT and URLs. Also, it was contemplated if the message was written in first, second and third person. With the above, it is expected that the features associated with the words added to those found in the usage profiles will improve the classifications.		

Features for Classification Model

	#	Feature	Description		
	1	stats_avg_word	Average word size per tweet		
	2	stats_kur_word	Kurtosis of the variable stats_avg_word		
	3	stats_label_emoji	Amount of emojis per tweet for the profile		
	4	stats_label_hashtag	Number of hastags per tweet for the profile		
	5	stats_label_mention	Number of mentions per tweet for the profile		
	6	stats_label_url	Number of urls per tweet for the profile		
	7	stats_label_retweets	Number of retweets per tweet for the profile		
	8	stats_lexical_diversity	Lexicon diversity for all tweets by profile		
	9	stats_label_word	Number of words per tweet for the profile		
	10	kurtosis_avg_word	Kurtosis of the variable stats_kur_word		
	11	kurtosis_label_word	Kurtosis of the variable stats_label_word		
_	12	skew_avg_word	Statistical asymmetry of the variable stats_avg_word		



Methodology System Training



Words Vector from Tweets

1) Network Features,

- 2) Lexical Features,
- 3) Sociolinguistic features
- 4) Text Tweet

Results

The novelty in the analysis presented in this paper is to analyze specific features of digital social networks for each profile. The use of sociolinguistic features in theuser profile has shown many quirks in topics social, cultural, and of gender. Thesecharacteristics describe the sociolect of celebrities linked in this study; we also find it is essential to understand if the text was written in the first, second or third person, and the lexical diversity that each profiles had.As future work, we plan to analyze the models with real samples with a similaror greater volume of messages. Finally, we want to review the posts and context datato have models that respond socially to variables that represent real phenomena in thenetwork.

Multi Thread Process by each Profile **Queue Profile** Vectorized words for all Uses of feature by each profile post, 18 new features. posts. GaussianNB ogisticRegression -MultinomialNB -Classifier **Join Features** RandomForest -Svm Save Best Models System Training Write stats End

Result Classifier Accuracy

Class Datase	et Training Data	aset Test1 Data	set Test2
Fame	0.82	0.56	0.51
Gender	0.64	0.64	0.56
Occupation	0.54	0.46	0.41
Birthyear	0.56	0.51) I ESSI	RE 0.51
C-Rank Che testals	0.63	0.54 PER	0.49

As shown in Table Result Classifier Accuracy, the models were tested using the training dataset, the test1 dataset and the test2 dataset. In the ranking of the task, we occupied the second position.

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