N-GrAM: New Groningen Author-profiling Model

Angelo Basile, Gareth Dwyer, Maria Medvedeva, Josine Rawee, Hessel Haagsma, and Malvina Nissim





Meet the Team

Task and Data

Our approach

Data insights

Conclusion

MEET THE TEAM

During and after writing

Malvina Nissim

(Head honcho)

Hessel Haagsma
 Masha Medvedeva

(PAN Veterans)

Gareth Dwyer Josine Rawee Angelo Basile

(PAN Newbies)





TASK AND DATA

Task and data

Twitter data:

- ~100 tweets/ author
- 600 authors / variety

Language	Varieties	Authors
Arabic	4	2400
English	6	3600
Portuguese	2	1200
Spanish	7	4200

Task and data

	Language	Varieties	Authors
Twitter data:	Arabic	4	2400
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Gender and Language Variety profiling

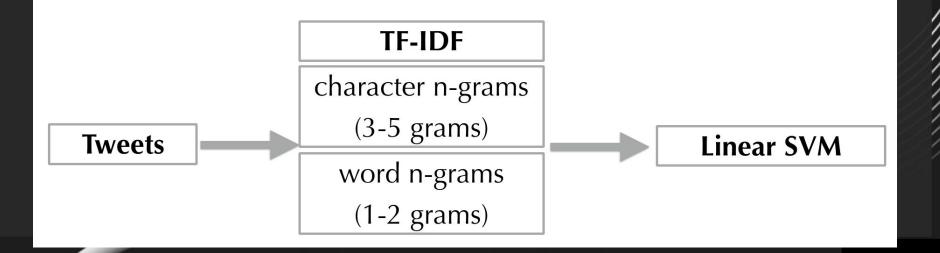
- Is the author Male or Female?
- What language variety are they using?

OUR APPROACH

N-grams + SVM

Start with basic system

- Word and Character n-gramsTF-IDF
- Linear Support Vector Machine





More data

- Previous PAN data
- Twitter14k dataset

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More features

- Tokenizers
- POS tags
- Twitter Handles + Place Names
- Emojis

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- Fast Text, Decision Trees, Neural Networks

More data is better data!



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Adding data from previous pan years

- Train on 2016, test on 2017
- Vice versa
- :(

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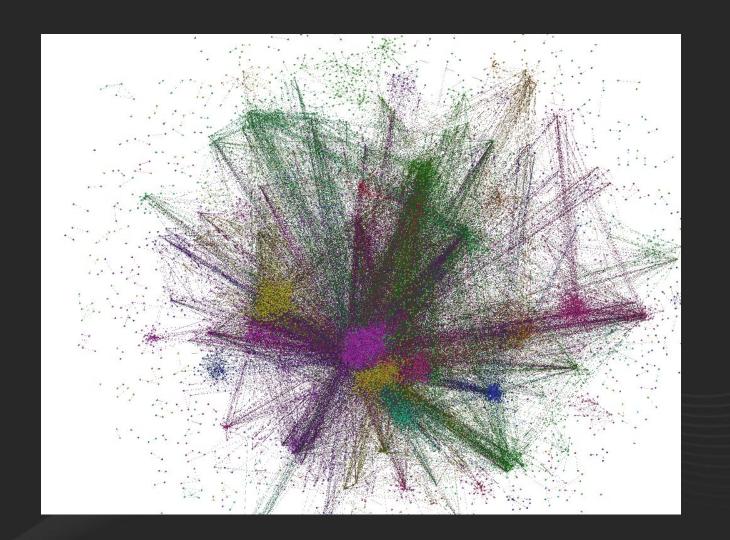
- Train on 2016, test on 2017
- Vice versa
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- :(

Add Twitter 14k dataset

- Typically 'male' and 'female' words

Adding features will help!



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Tokenizers

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- Happy Fun Tokenizer (emoticons)
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POS Tags

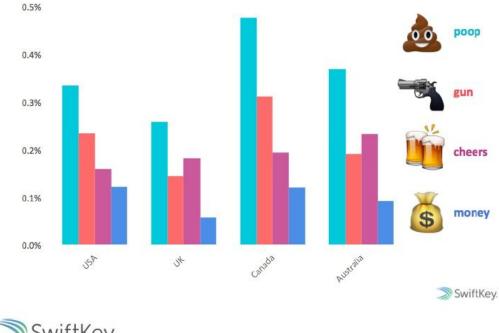
- :(

Twitter Handles + Place names (Variety)

- Collect corpus of associations with common towns/ handles

More Features (2)

Emoji - SwiftKey report - :(

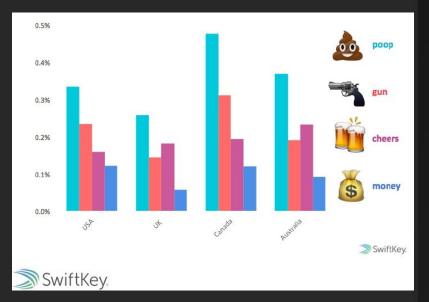




More Features (2)

Emoji

SwiftKey report:(



GronUP

- Punctuation, word length, capitals, vocabulary, etc, etc
- :(

More data

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- Twitter14k dataset

More features

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- Twitter Handles + Place Names
- Emojis

More classifiers

- Neural Networks (!!!!!)

More Classifiers

- FastText
 - It's fast!
 - :(

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scikit-learn MLP

- Not so fast
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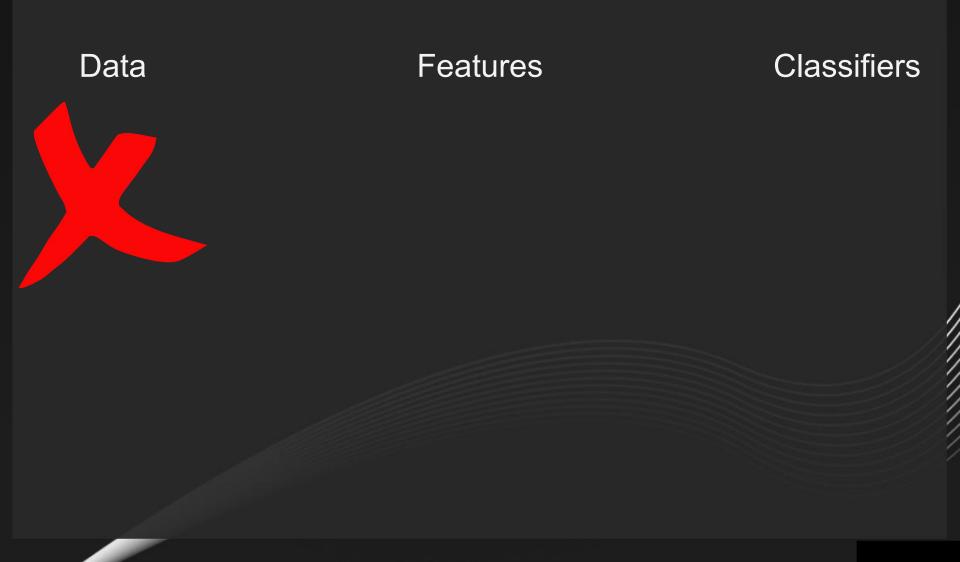
Keras

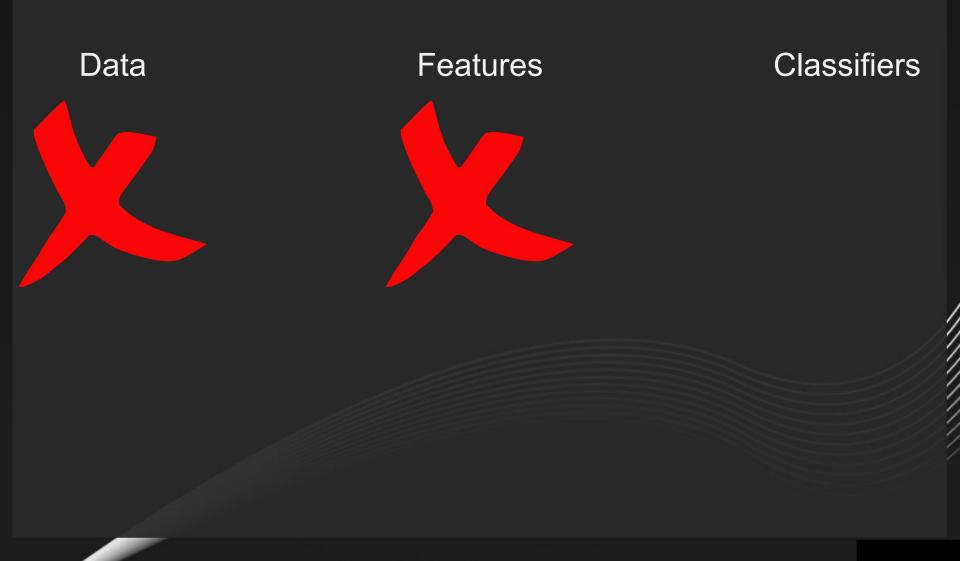
- Had fun with generative models
- :(

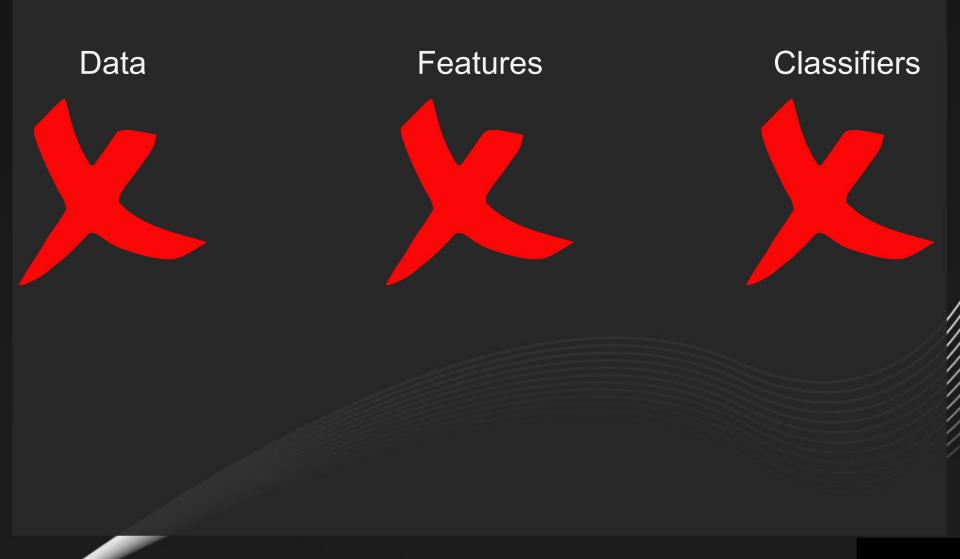
Data

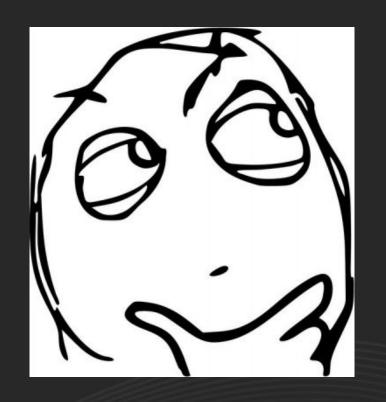
Features

Classifiers









Grid search for results

64 cores, 1TB RAM, 1 day

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Tune parameters per language / task ?

- Not necessary this time

Grid search for results

64 cores, 1TB RAM, 1 day

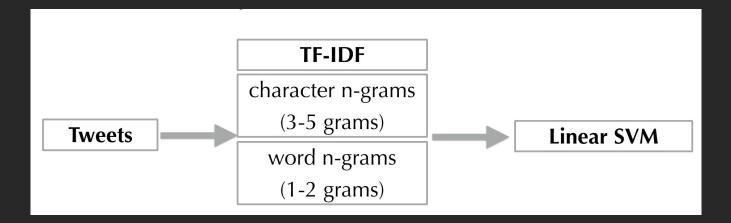
Tune parameters per language / task ?

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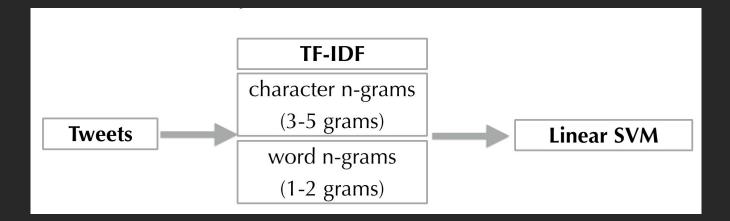
Scikit-learn defaults are well chosen

- min_df=2, sublinear_tf=True

Start



End



Results

Task	System	Arabic	English	Portuguese	Spanish	Average	+ 2nd
Variety	N-GrAM	0.8313	0.8988	0.9813	0.9621	0.9184	0.0013
	LDR	0.8250	0.8996	0.9875	0.9625	0.9187	
Gender	N-GrAM	0.8006	0.8233	0.8450	0.8321	0.8253	0.0029
	LDR	0.7044	0.7220	0.7863	0.7171	0.7325	
Joint	N-GrAM	0.6831	0.7429	0.8288	0.8036	0.7646	0.0101
	LDR	0.5888	0.6357	0.7763	0.6943	0.6738	

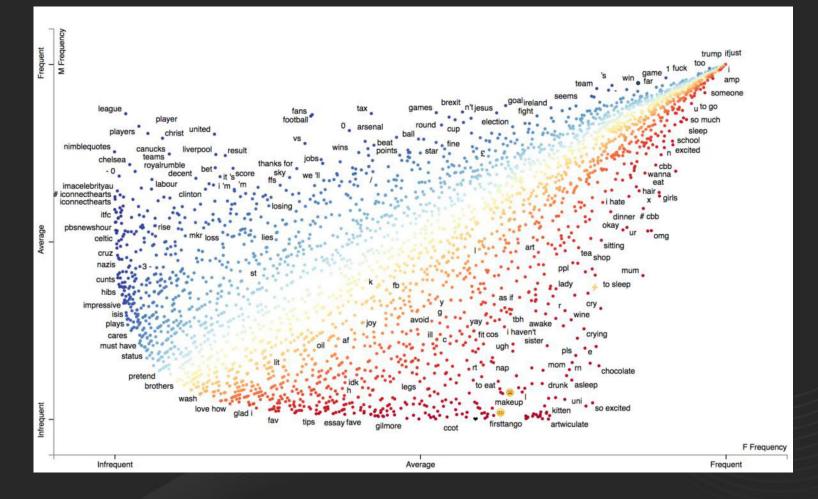
DATA INSIGHTS

Stereotypes ahead!

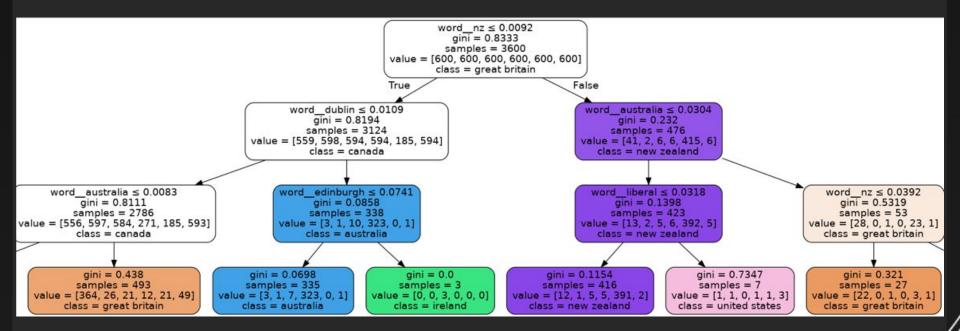


YOUR ASSUMPTIONS ABOUT ME MAY BE DISTORTED BY EXPOSURE TO OUTDATED GENDER STEREOTYPES

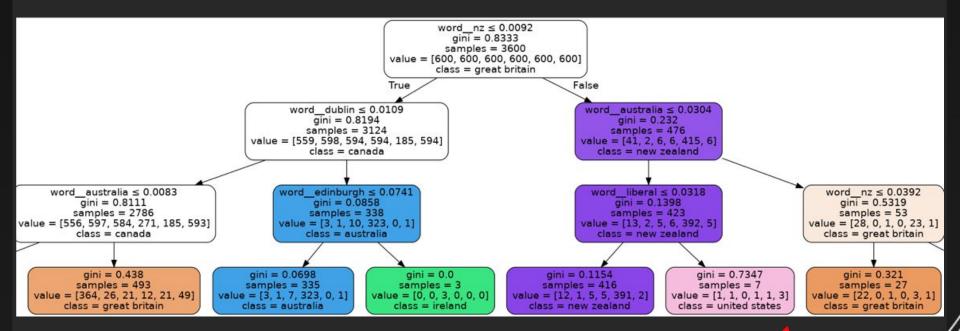
English gender visualisation



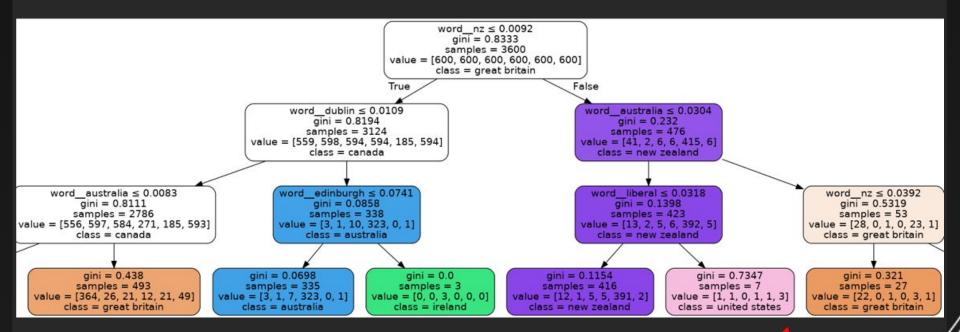
Made with https://github.com/JasonKessler/scattertext



Colour/color? lift/elevator? Toilet/Loo/WC/Dunny?

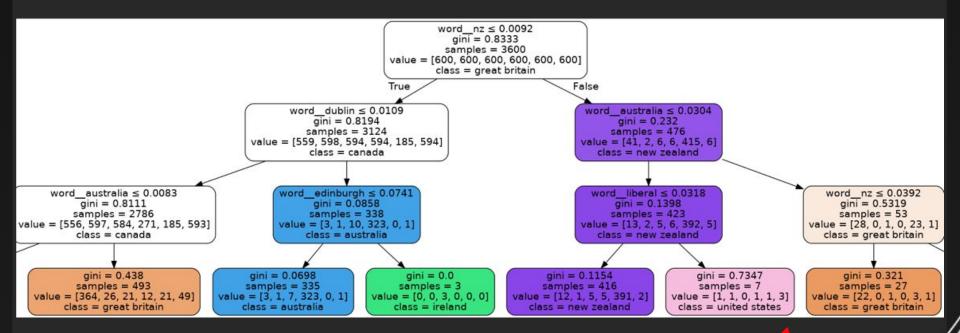


Colour/color? lift/elevator? Toilet/Loo/WC/Dunny?



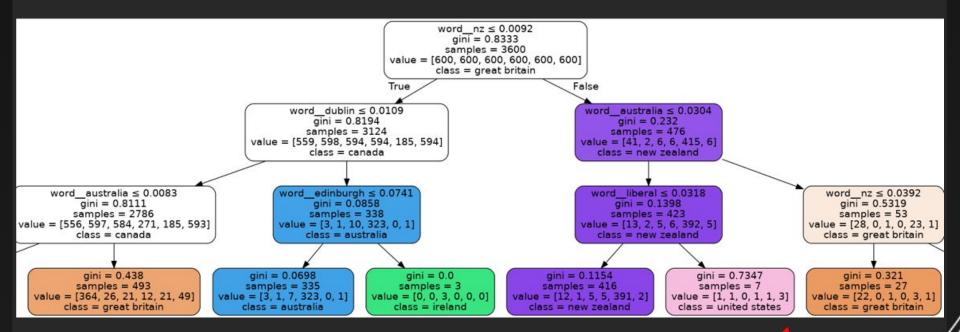
Colour/color? lift/elevator? Toilet/Loo/WC/Dunny?

"Australia"



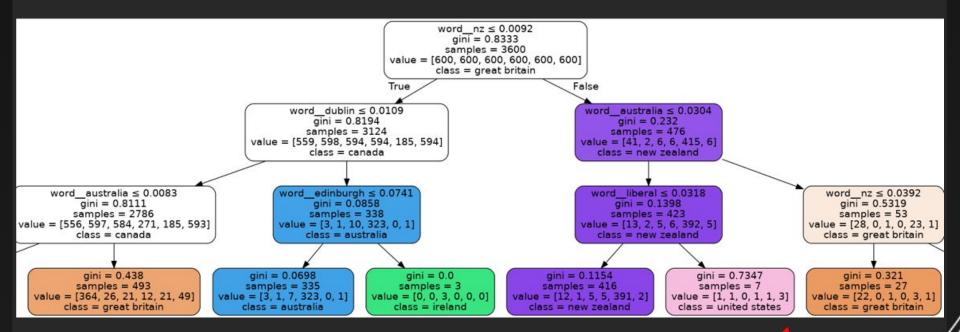
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"Australia", "Dublin"



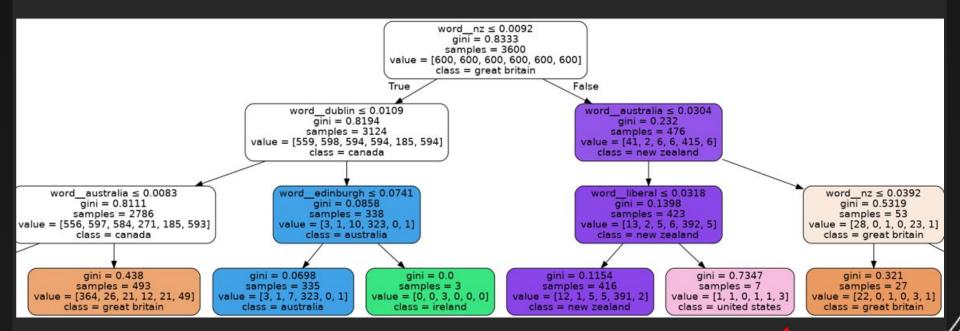
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"Australia", "Dublin", "NZ"



Colour/color? lift/elevator? Toilet/Loo/WC/Dunny?

"Australia", "Dublin", "NZ", "Edinburgh"



Colour/color? lift/elevator? Toilet/Loo/WC/Dunny?

"Australia", "Dublin", "NZ", "Edinburgh", "Liberal"

CONCLUSION

N-grams + SVM is (still?) a powerful combo

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Adding data and features doesn't always help (and can harm)

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Neural Networks are tricky

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Neural Networks are tricky

Assumptions are wrong



Questions? Suggestions? Answers? Money?

*With apologies to James Connan