Predicting Race and Ethnicity From Sequence of Characters in a Name

March 23, 2019

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- Flip side: Instrument for Discrimination

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  - Common Sequences: `da_as_sh_ia_an`, `ne_ej_ja_ad`, `sa_ad_eh`, `jo_oh_ha_an_ns_se_en`

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  - Wikipedia Data

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		Last Name	Full Name
Race	Asian	.54	.60
	Hispanic	.72	.75
	NH Black	.32	.55
	NH White	.88	.90

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Application

Percentage Donated to Political Campaigns in 2000 and 2010 by People of Different Races/Ethnicities.

	Census		Florida	
race	2000	2010	2000	2010
asian	2.22%	2.74%	2.00%	2.28%
black	11.04%	10.22%	8.93%	7.92%
hispanic	3.24%	4.32%	3.23%	3.31%
white	83.49%	82.71%	85.84%	86.49%

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- API call for Model Performance on Benchmarks
- Failsafe on predictions

Python Package

```
> import pandas as pd
> from ethnicolr import census_ln, pred_census_ln
Using TensorFlow backend.
> names = [‘name’: ‘smith’,
... ‘name’: ‘zhang’,
... ‘name’: ‘jackson’]
> df = pd.DataFrame(names)
> census_ln(df, ‘name’, 2010)
```

name	race	pctwhite	pctblack	pctapi
smith	white	70.9	23.11	0.5
zhang	api	0.99	0.16	98.06
jackson	black	39.89	53.04	0.39

Last Words

Thank you!