Language detection using character n-gram profiles Inspiration from Cavnar and Trenkle (1994)

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Overview

- Introduction
- Methodology
- **3** Results
- 4 Discussion
- **5** Conclusions

Motivation

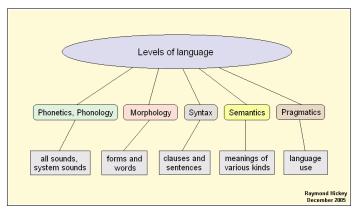


Figure 1: Levels/structures of languages; figure taken from Hickey (2005)

- Morphological profiling probably has lower data and compute requirements
- Makes sense given no external libraries are allowed

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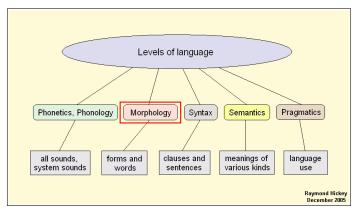


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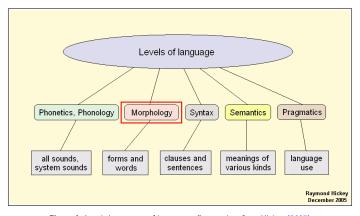


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Methodology

- Character n-gram profiling technique from Cavnar, Trenkle, et al. (1994)
- WiLI-2018 data set for 235 languages with 235,000 paragraphs (Thoma, 2018)
- Similarities: Data is lower-cased and punctuation/special-tokens are removed
- Differences: Use vector-based difference norm instead of out-of-place distance
- Two hyperparameters: character n-gram length and ranked n-gram cutoff

N-Gram-Based Text Categorization

William B. Cavnar and John M. Trenkle Environmental Research Institute of Michigan P.O. Box 134001 Ann Arbor MI 48113-4001

Figure 2: Excerpt from Cavnar, Trenkle, et al. (1994)



Figure 3: Flowchart from Cavnar, Trenkle, et al. (1994

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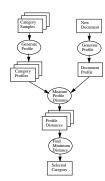


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Results

N-gram length	N-gram cutoff	Weighted Test F ₁	Best Language	Worst Language
2	100	0.865	Navajo	Konkani
2	300	0.893	Navajo	Pampanga
3	100	0.859	Dhivehi	Chavacano
3	300	0.898	Navajo	Chavacano

Table 1: Tabular summary of model performances; MLP from Thoma (2018) achieved an accuracy of 0.883

Language	N_1	N_2	N_3	\mathbb{N}_4	N_5
English	the	and			ent
Deutsch	der				
Italiano			ent		lla

Table 2: Tabular summary of top five character trigrams with highest relative frequency per language

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Gold language	Utterance	Predicted language
English	What is this?	Cantonese
Deutsch	Was ist das?	Chavacano
Italiano	Cos'è questo?	Asturian

Table 3: Examples of erroneous language detection for short phrases

Plenty of failing cases:

- Short phrases where language profile cannot converge
- Slang, colloquial or borrowed words
- Transliteration from non-Latin to Latin script

Plenty of workarounds

- Word-level language identification with large-enough vocabulary
- Complex modeling over sequential subwords, for example using neural networks;
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- Portable and lightweight character n-gram profiling technique from Cavnar, Trenkle, et al. (1994)
- Trained and tested on WiLI-2018 (Thoma, 2018)
- Best character trigram model achieved 89.8% weighted F₁ test score
- Works well for medium-long length documents, likely robust to previously unseen words and spelling errors
- Known limitations on short length documents

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Bibliography I

- Bartz, Christian, Tom Herold, Haojin Yang, and Christoph Meinel (2017). "Language Identification Using Deep Convolutional Recurrent Neural Networks". In: CoRR abs/1708.04811. arXiv: 1708.04811. URL: http://arxiv.org/abs/1708.04811.
- Cavnar, William B, John M Trenkle, et al. (1994). "N-gram-based text categorization". In: *Proceedings of SDAIR-94, 3rd annual symposium on document analysis and information retrieval.* Vol. 161175. Citeseer.
- Hickey, Raymond (2005). "Levels of language". In: Universität Duisburg-Essen.
- Thoma, Martin (2018). "The WiLl benchmark dataset for written language identification". In: arXiv preprint arXiv:1801.07779.