How many languages can a language model model?

Robert Östling

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- Dammit, Google! (Johnson et al., arXiv 2016-11-14)
  shared parameters, shared "vocabularies"

A proposition

Let's use language vectors for multilingual NLP

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   - $P(t_{dog} = \text{noun} | v_{eng}) = 0.9$ implies that $P(t_{dog} = \text{noun} | v_{eng} + \epsilon) \approx 0.9$

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  - Sentence vectors (problem: predict semantic equivalence)

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- Target words y_t are predicted using

$$
\begin{aligned}
P(y_t|h_t) &\propto \exp(Wh_t + b) \\
i &= \sigma(W_i x_t + U_i h_{t-1} + b_i) \\
f &= \sigma(W_f x_t + U_f h_{t-1} + b_f) \\
o &= \sigma(W_o x_t + U_o h_{t-1} + b_c) \\
c &= \tanh(W_c x_t + U_c h_{t-1} + b_c) \\
c_t &= fc_{t-1} + ic \\
h_t &= o \tanh(c_t)
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- Johnson et al. independently did essentially the same thing by adding a special language selection token in an NMT model (the main difference is that their model has to access the language vector through the attention mechanism and/or hidden LSTM states)

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  - high named entity overlap

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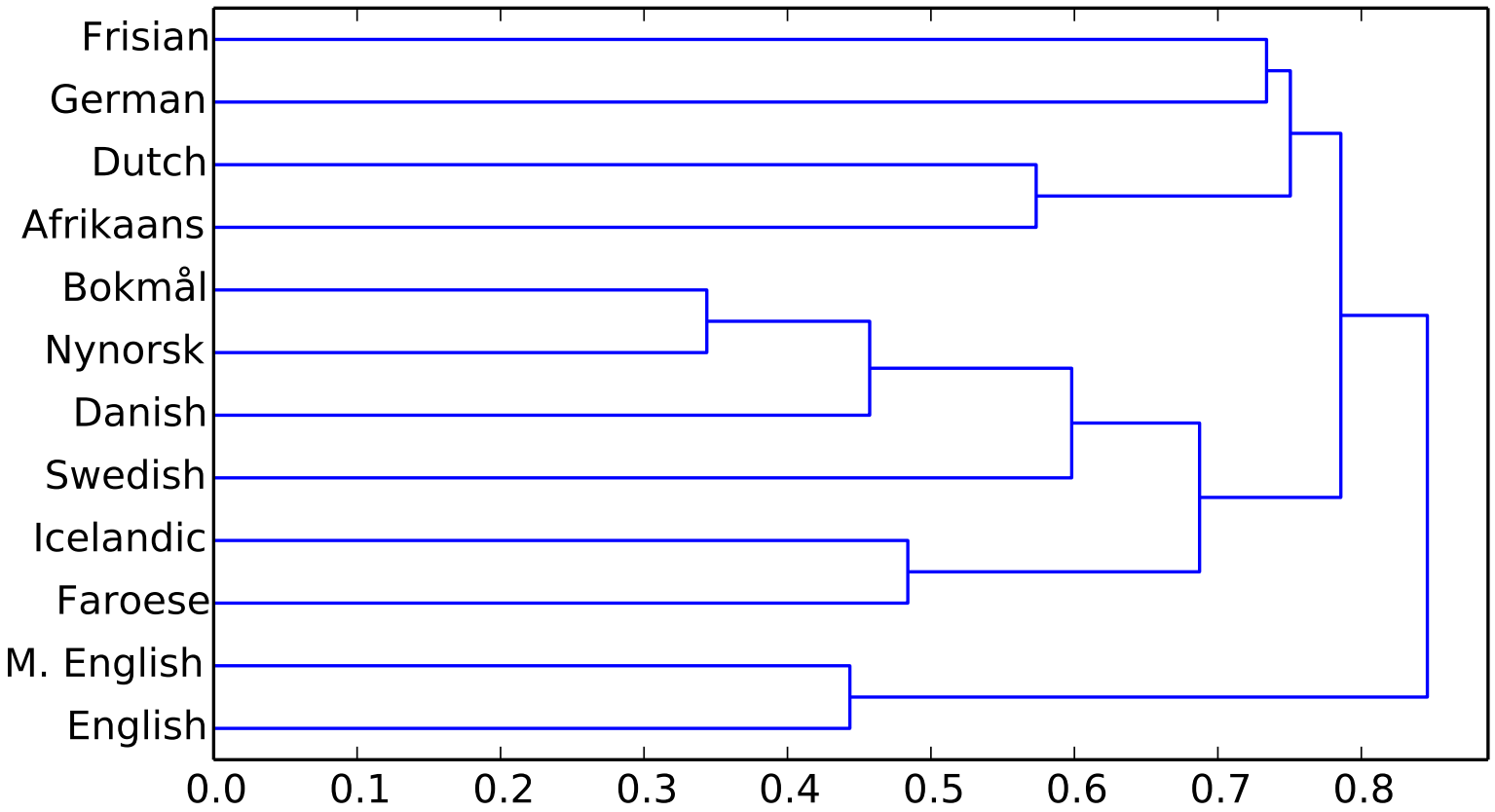
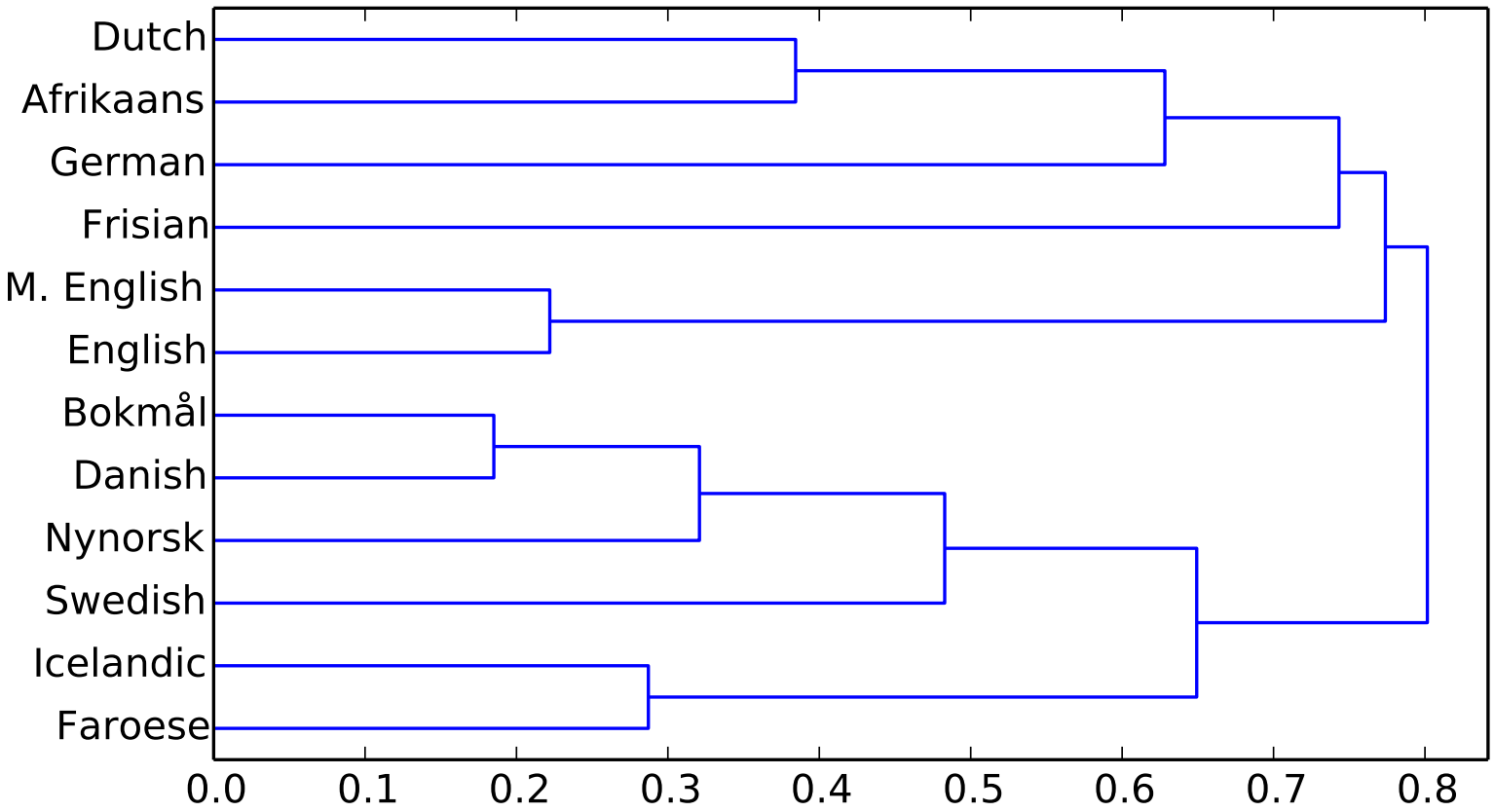
- This takes time (several days on a GPU for large models)

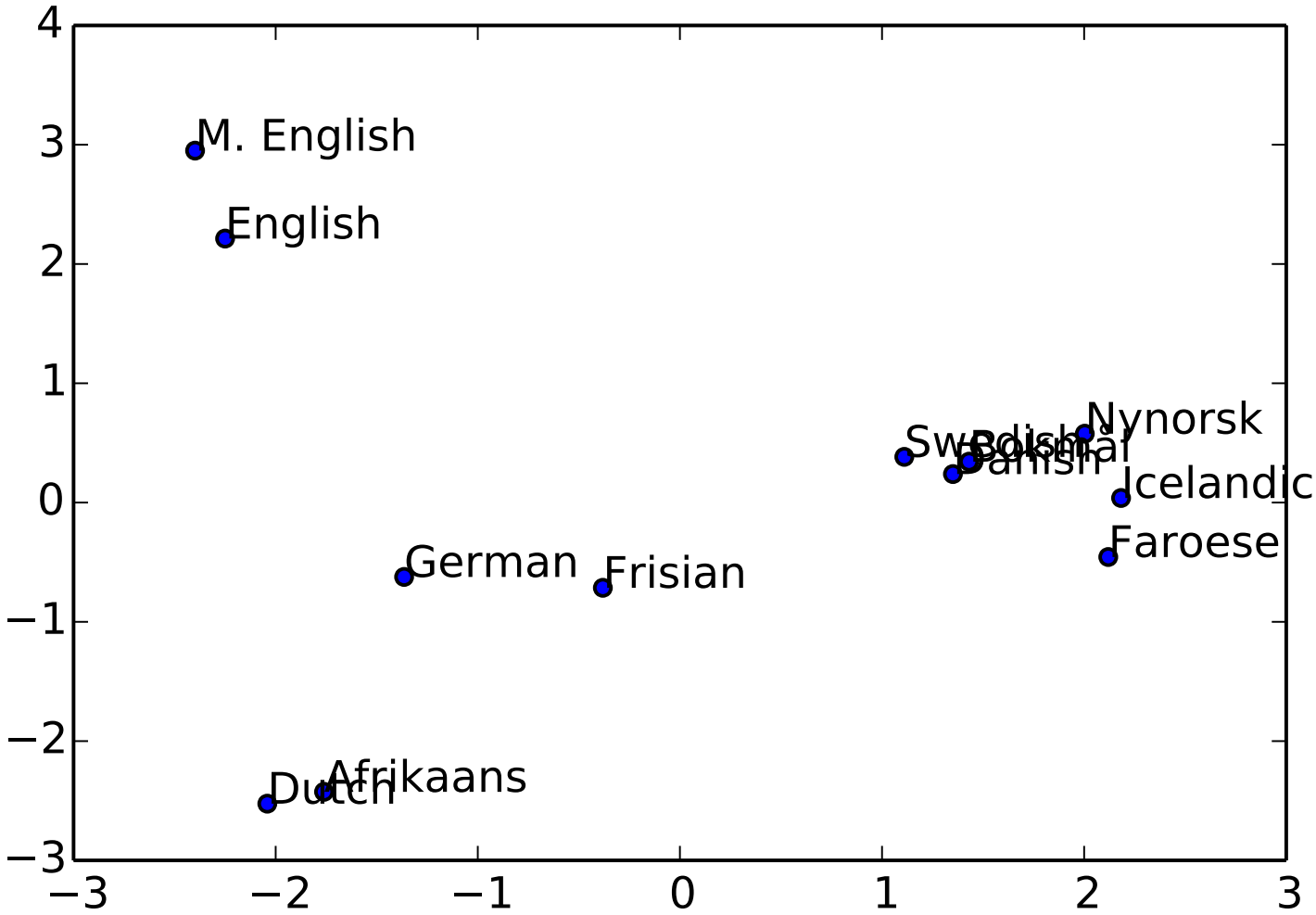
First light


Frisian
German
Dutch
Afrikaans
Bokmål
Nynorsk
Danish
Swedish
Icelandic
Faroese
M. English
English
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8

Smaller model, separate initialization



Same data as before, using PCA



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  - **0.56**: therefore, behold, i will lose the sound of my soul, and i will not fight it into the land of egypt

Another angle

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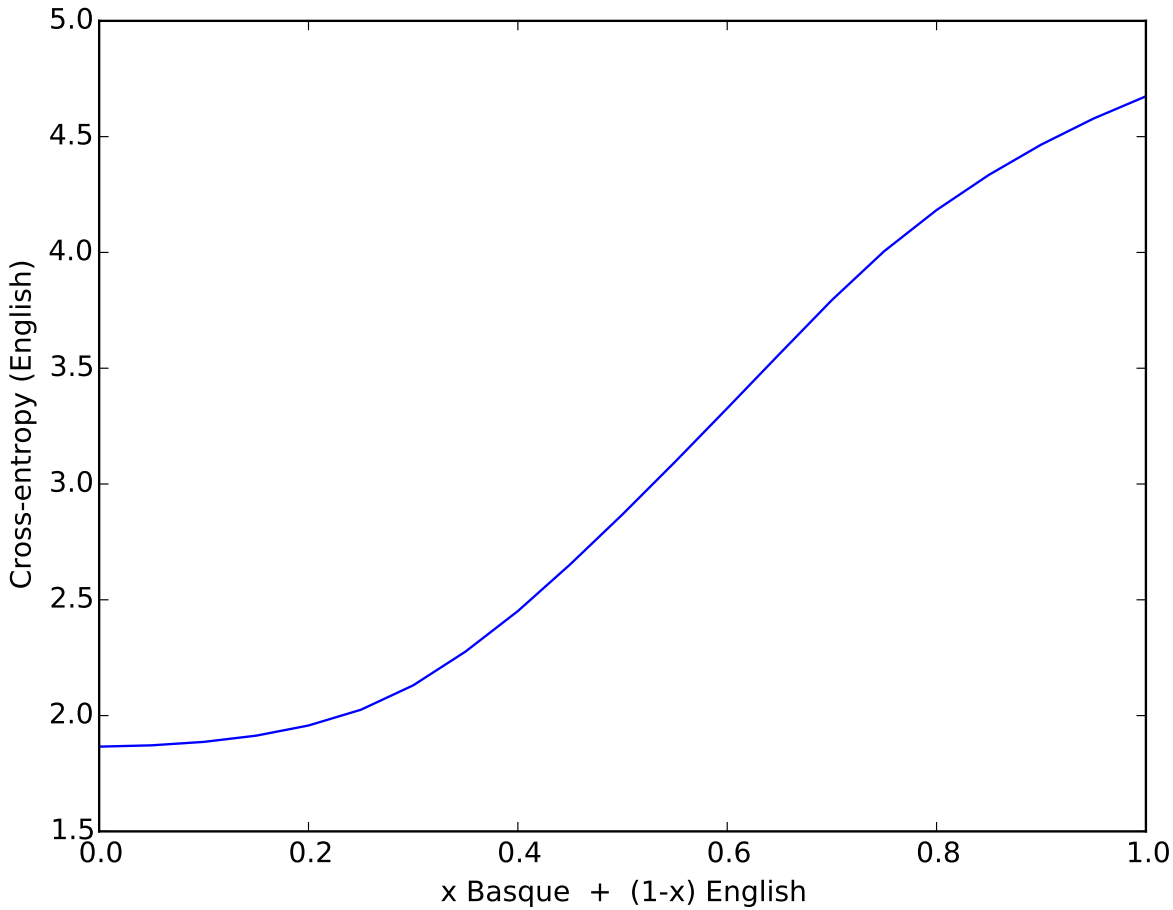
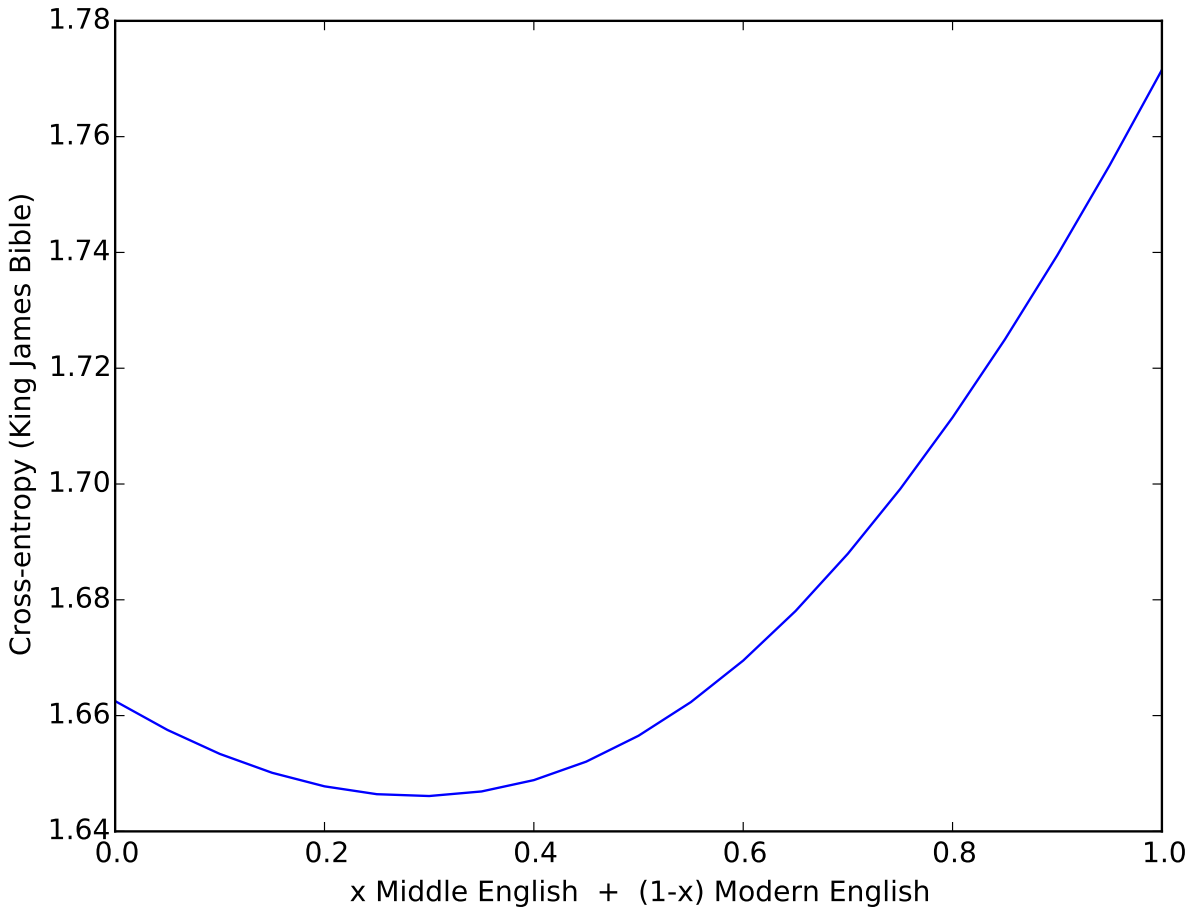
- Let's plot cross-entropy over a line in language space...

English is not Basque



Where's King James?



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