What Kind of Language Is Hard to Language-Model?

ACL 2019

Sabrina J. Mielke and Ryan Cotterell, Kyle Gorman, Brian Roark, Jason Eisner

Johns Hopkins University // City University of New York Graduate Center // Google
sjmielke@jhu.edu

Twitter: @sjmielke – paper and thread pinned!
0. Do current language models do equally well on all languages?

No.

1. Which one do they struggle more with: German or English?

German.

2. What about non-Indo-European languages, say Chinese?

It depends.

3. What makes a language harder to model?

Actually, rather technical factors.

4. Is Translationese easier?

It's different, but not actually easier!
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“Difficulty”
Outline

“Difficulty”

Models and languages
Outline

“Difficulty”

Models and languages

What correlates with difficulty?
What correlates with difficulty?

And... is Translationese really easier?
How to measure “difficulty”?

Language models measure surprisal/information content (NLL; $-\log p(\cdot)$):

\[ p(\cdot) \Rightarrow \text{NLL} \]

<table>
<thead>
<tr>
<th>$en$</th>
<th>I love Florence!</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.03</td>
<td>$\Rightarrow$ 5 bits</td>
</tr>
</tbody>
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Issue 1: Different topics/styles/content

Solution: train and test on translations!

Europarl: 21 languages share ~40M chars

Bibles: 62 languages share ~4M chars

and this one takes a big ILP to solve, which is really fun

Gurobi

\[ \sum_{69 \text{ languages}} 13 \text{ language families} \]
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Issue 2: Comparing scores

Use total bits of an open-vocabulary model.

Why?
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</tr>
<tr>
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<td>6.3</td>
</tr>
<tr>
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   [note: total easily obtainable from BPC or perplexity by multiplying with total chars/words]
How to aggregate multiple intents’ surprisals into “difficulties”? 

For fully parallel corpora...

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<td>Въобновяване на се- ...</td>
</tr>
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aligned multi-text
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LM surprisals/NLLs

- $y_{1,\text{en}}$
- $y_{1,\text{de}}$
- $y_{1,\text{bg}}$
- $y_{2,\text{en}}$
- $y_{2,\text{de}}$
- $y_{2,\text{bg}}$
- $y_{3,\text{en}}$
- $y_{3,\text{de}}$
- $y_{3,\text{bg}}$
- $y_{4,\text{en}}$
- $y_{4,\text{de}}$
- $y_{4,\text{bg}}$
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For fully parallel corpora... we can just sum everything up and compare – that is fair.

aligned multi-text

<table>
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<th>Wieder-</th>
<th>Възобновяване</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>aufnah-</td>
<td>на се-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>me der</td>
<td></td>
</tr>
<tr>
<td>2</td>
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</tr>
<tr>
<td></td>
<td>…</td>
<td>gestezn</td>
<td>бе</td>
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<td>…</td>
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<td>бяхме</td>
</tr>
<tr>
<td></td>
<td>not</td>
<td>nicht</td>
<td></td>
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\[ \sum_{\text{en}} \sum_{\text{de}} \sum_{\text{bg}} \]
How to aggregate multiple intents’ surprisals into “difficulties”?

But what if there’s missing data? Or we want robustness?

aligned multi-text

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<td>me der</td>
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LM surprisals/NLLs

\[
\begin{align*}
Y_{1,\text{en}} & \quad Y_{1,\text{de}} \\
Y_{2,\text{en}} & \quad Y_{2,\text{de}} \quad Y_{2,\text{bg}} \\
Y_{3,\text{de}} & \quad Y_{3,\text{bg}} \\
Y_{4,\text{en}} & \quad Y_{4,\text{bg}}
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Language model

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aligned multi-text

LM surprisals/NLLs

\[ y_{1,\text{en}} \rightarrow n_1 \]
\[ y_{1,\text{de}} \]
\[ y_{2,\text{en}} \rightarrow n_2 \]
\[ y_{2,\text{de}} \]
\[ y_{2,\text{bg}} \]
\[ y_{3,\text{de}} \rightarrow n_3 \]
\[ y_{3,\text{bg}} \]
\[ y_{4,\text{en}} \rightarrow n_4 \]
\[ y_{4,\text{bg}} \]

\[ d_{\text{en}} \]
\[ d_{\text{de}} \]
\[ d_{\text{bg}} \]
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aligned multi-text

1

2

3

4

LM surprisals/NLLs

\[ \sum_{en} \Rightarrow n_1 \]

\[ n_2 \]

\[ n_3 \]

\[ n_4 \]

\[ d_{en} \]

\[ d_{de} \]

\[ d_{bg} \]

Resumption of the session

Wiederaufnahme der ...

The peace that ...

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**language model**

**LM surprisals/NLLs**

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\[ y_{3,\text{bg}} \rightarrow n_3 \]

\[ y_{4,\text{en}} \rightarrow n_4 \]

\[ y_{4,\text{bg}} \rightarrow n_4 \]

\[ y_{4,\text{en}} \rightarrow n_4 \]

\[ d_{\text{en}} \]

\[ d_{\text{de}} \]

\[ d_{\text{bg}} \]
How to aggregate multiple intents’ surprisals into “difficulties”?

But what if there’s missing data? Or we want robustness?

The image shows a table of aligned multi-text across languages (en, de, bg) with surprisal values for each language. The surprisal values are aggregated to calculate the total surprisal for each language:

\[ n_1 = \sum \text{en} \]
\[ n_2 = \sum \text{de} \]
\[ n_3 = \sum \text{bg} \]

For language de, the surprisal is calculated as:

\[ y_{2,\text{de}} = n_2 \cdot \exp d_{\text{de}} \]

This is a probabilistic model we can perform inference in!
How to aggregate multiple intents’ surprisals into “difficulties”?

But what if there’s missing data? Or we want robustness?

Resumption of the session
Wieder aufnahme der ...

The peace that ...
Der gute verein ...

Obwohl wir nicht ...
Макар че не бяхме ...

Now we can finally ...
Накрая всички можем ...

This is a probabilistic model we can perform inference in!

 vowed multi-text
How to aggregate multiple intents’ surprisals into “difficulties”?

But what if there’s missing data? Or we want robustness?

Not quite, our actual model is HETEROSCEDASTIC:

\[ y_{ij} = n_i \cdot \exp(d_j) \cdot \exp(\varepsilon_{ij}) \]

\[ \sigma_i^2 = \ln \left( 1 + \frac{\exp(\sigma^2) - 1}{\sigma^2} \right) \]

\[ \varepsilon_{ij} \sim \mathcal{N} \left( \frac{\sigma^2 - \sigma_i^2}{2}, \sigma_i^2 \right) \]
“Difficulty”

What correlates with difficulty?

And... is Translationese really easier?

Models and languages
Formerly state-of-the-art-ish AWD-LSTM (Merity et al., 2018) language models:

char-RNNLM:
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BPE-RNNLM, few merges:
Formerly state-of-the-art-ish AWD-LSTM (Merity et al., 2018) language models:

- **char-RNNLM:**
  
  - The cat chased

- **BPE-RNNLM, few merges:**
  
  - the cat @ chase

- **BPE-RNNLM, many merges:**
  
  - the cat chase
Choosing the number of BPE merges: how many is best?

It depends on the language (total surprisal, given merges as a ratio of the vocabulary):
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It doesn't matter that much.

chars

average
Choosing the number of BPE merges: how many is best?

It depends on the language (total surprisal, given merges as a ratio of the vocabulary):

![Graph showing BPE merges for different languages]

Yeah:

it doesn’t matter that much.

is this one going to be fine?
Difficulties for char-/BPE-RNNLM: 21 Europarl languages

Difficulties on Europarl

difficulty (×100) using BPE-RNNLM

difficulty (×100) using char-RNNLM

-8 -6 -4 -2 0 2 4 6 8 10

-4 -3 -2 -1 0 1 2 3 4 5
Di/uniFB03culties for char-/BPE-RNNLM: 21 Europarl languages

easier with BPE

easier with chars
Difficulties for char-/BPE-RNNLM: 21 Europarl languages

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difficulty (×100) using BPE-RNNLM with 0.4|V| merges
Difficulties for char-/BPE-RNNLM: 21 Europarl languages
Difficulties for char-/BPE-RNNLM: 21 Europarl languages and Bibles

![Difficulties on Europarl](image)

![Difficulties on Bibles](image)

- Easier with BPE
- Easier with chars
Difficulties for char-/BPE-RNNLM: 21 Europarl languages and 106 Bibles

easier with BPE

easier with chars

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Models and languages

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How about: morphological counting complexity (Sagot, 2013)

...not particularly striking. Perhaps Finnish was an outlier in Cotterell et al. (2018)?
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Other linguistically motivated regressors

WALS: “Prefixing vs. Suffixing [...] Morphology” (for languages where present)?
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This is disappointing.
Very simple heuristics are very predictive

Raw sequence **length / # predictions**
→ **char-RNNLM difficulty**

**Significant on:**
- Europarl at $p < .01$
- Bibles at $p < .001$

i.e., for the char-RNNLM
puč_{cz} is easier than Putsch_{de}!
Very simple heuristics are very predictive

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i.e., the BPE-RNNLM still suffers if a language has high type-token-ratio!
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Wow! What is happening here? We have many conjectures...
“Difficulty”

Models and languages

What correlates with difficulty?

And... is Translationese really easier?
Common assumption: Translationese is somehow simpler than “native” text.
**Translationese: translations as a separate language?**

*Common assumption: Translationese is somehow simpler than “native” text.*

We have partial parallel data that we can use to evaluate our models:

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...and indeed the original languages **seem** harder.
Translationese: translations as a separate language?

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...and indeed the original languages seem harder.  *But we missed something!*
We trained on mostly translationese!

Of course we will then find it easier...
Repeat the experiment with fairly balancing training data

Change the training sets!

We can **rebalance a single language**, leaving the others merged, i.e.:

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And the result: the **difficulties are now the same**!

(more precisely, “native” is $0.004 \pm 0.02$ easier)
Conclusion: cross-linguistic comparisons are tricky  (hope we didn’t mess up!)
1. Make sure your training data is comparable and fair.
Conclusion: cross-linguistic comparisons are tricky  (hope we didn’t mess up!)

1. Make sure your training data is comparable and fair.
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1. Make sure your training data is comparable and fair.
2. Make sure your metrics are comparable and fair.
3. Make sure your stats are fair (no p-hacking!).
4. Work on more NLP resources for more languages!
What Kind of Language Is Hard to Language-Model?

ACL 2019

Sabrina J. Mielke and Ryan Cotterell, Kyle Gorman, Brian Roark, Jason Eisner

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sjmielke@jhu.edu

Twitter: @sjmielke – paper and thread pinned!