Are All Languages Equally Hard to Language Model?

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Problem with Bits Per Character

$$p(\texttt{the cat sat on the mat}) = 0.000000000341$$
$$p(\texttt{the mat sat on the cat}) = 0.000000000239$$
$$p(\texttt{the cat the on mat mat}) = 0.000000000001$$

$$ppl_{word} = \exp \frac{-\log 0.000000000341}{6+1} = 22.5$$

$$ppl_{word} = \exp \frac{-\log 0.000000000341}{22+1} = 2.7$$

$$p(\texttt{the}|\varepsilon) = 0.01$$
$$p(\texttt{cat}|\texttt{the}) = 0.001$$
$$p(\texttt{sat}|\texttt{the cat}) = 0.008$$
$$p(\text{EOS}|\texttt{the cat sat}) = 0.04$$

$$\Rightarrow p(\texttt{the cat sat}) = 0.1 \cdot 0.01 \cdot 0.008 \cdot 0.04 = 0.00000032$$

1 Introduction

Open Vocab vs Clsed Vocab

$$p_{word}(\texttt{the wolpertinger sat}) < p_{char}(\texttt{the wolpertinger sat})$$

"wolpertinger" is an oov

Therefore, the word-level language model will not assign probability to the word "wolpertinger"

$$p_{word}(\texttt{the cat sat}) > p_{char}(\texttt{the cat sat})$$

However when the in-domain word comes in, word-level will likely assign high probability

In other words, character-level LM's support doesn't match that of word-level LM's

2 Experiment

Fair evaluation metric across different languages?

Standard Perplexity(Bits Per Character)

$$\frac{1}{|\boldsymbol{c}|+1}\sum_{i=1}^{|\boldsymbol{c}|+1}\log p(c_i \mid \boldsymbol{c}_{<i})$$

Czech *puč* > German *Putsch.*

Proposed Metric(Bits Per English Character)

$$\frac{1}{|\boldsymbol{c}_{English}|+1}\sum_{i=1}^{|\boldsymbol{c}|+1}\log p(c_i \mid \boldsymbol{c}_{<i})$$

2 Experiment

MCC and Evaluation Table

			BPEC / ΔBPC (e-2)			
	data (M)		hybrid n-gram		LSTM	
lang	wds / ch	MCC	form	lemma	form	lemma
bg	0.71/4.3	96	1.13/ 4	1.03/ 1	0.95/ 3	0.80/ 1
cs	0.65/3.9	195	1.20/ -8	1.05/-12	0.97/ -6	0.83/ -9
da	0.70/4.1	15	1.10/ -1	1.06/ -4	0.85/ -1	0.82/ -3
de	0.74/4.8	38	1.25/ 17	1.18/ 13	1.04/ 14	0.90/ 10
el	0.75/4.6	50	1.18/ 13	1.08/ 5	0.90/ 10	0.82/ 4
en	0.75/4.1	6	1.10/ 0	1.08/ -3	0.85/ 0	0.83/ -3
es	0.81/4.6	71	1.15/ 12	1.07/ 7	0.87/ 9	0.80/ 5
et*	0.55/3.9	110	1.20/ -8	1.11/-15	0.97/ -6	0.89/-12
fi*	0.52/4.2	198	1.18/ 2	1.02/-11	1.05/ 1	0.79/ -9
fr	0.88/4.9	30	1.13/ 17	1.06/ 13	0.92/ 14	0.78/ 10
hu*	0.63/4.3	94	1.25/ 5	1.12/ -9	1.09/ 5	0.89/ -7
it	0.85/4.8	52	1.15/ 16	1.08/ 14	0.96/ 14	0.79/ 10
lt	0.59/3.9	152	1.17/ -6	1.12/ -7	0.93/ -5	0.88/ -6
lv	0.61/3.9	81	1.15/ -6	1.04/ -9	0.91/ -5	0.81/ -7
nl	0.75/4.5	26	1.20/ 11	1.16/ 4	0.92/ 8	0.91/ 4
pl	0.65/4.3	112	1.21/ 6	1.09/ -1	0.97/ 5	0.84/ -1
pt	0.89/4.8	77	1.17/ 16	1.09/ 9	0.88/ 12	0.82/ 7
ro	0.74/4.4	60	1.17/ 8	1.09/ 0	0.90/ 6	0.84/ 0
sk	0.64/3.9	40	1.16/ -6	1.06/-11	0.92/ -5	0.87/ -9
sl	0.64/3.8	100	1.15/-10	1.02/-10	0.90/ -8	0.80/ -7
sv	0.66/4.1	35	1.11/ -2	1.06/ -8	0.86/ -2	0.83/ -7

```
n.lemmatize('dies', 'v')
```

```
'die'
```

```
n.lemmatize('watched', 'v')
```

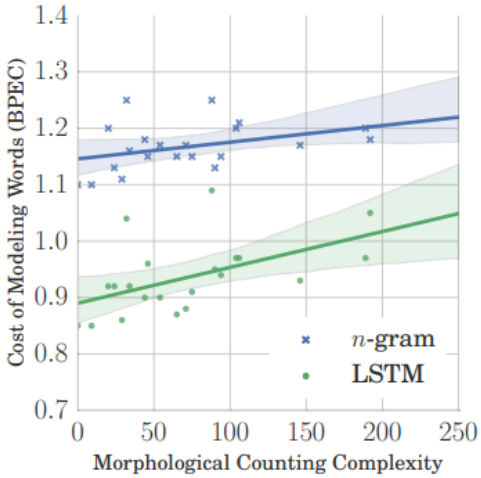
```
'watch'
```

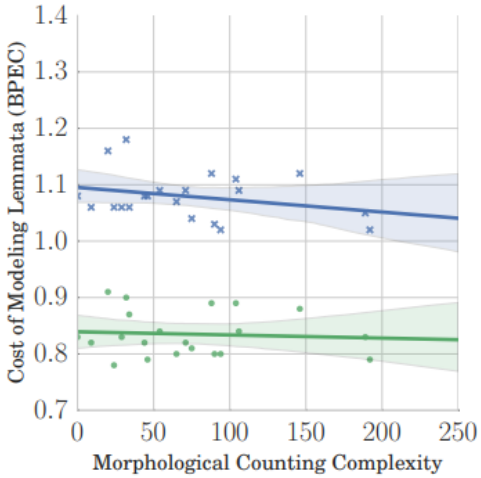
```
n.lemmatize('has', 'v')
```

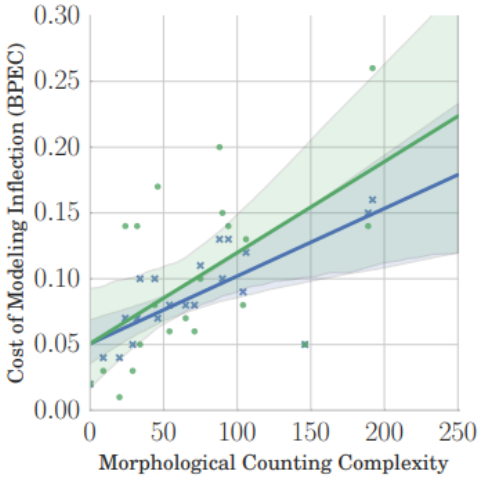
```
'have'
```

2 Experiment

Experiment Result







- High Counting Complexity results in high BPEC
- If lemmatized, no correlation between counting complexity and BPEC
- Inflectional morphology is the main culprit