

Preliminary Study on Automatic Grammaticality Evaluation

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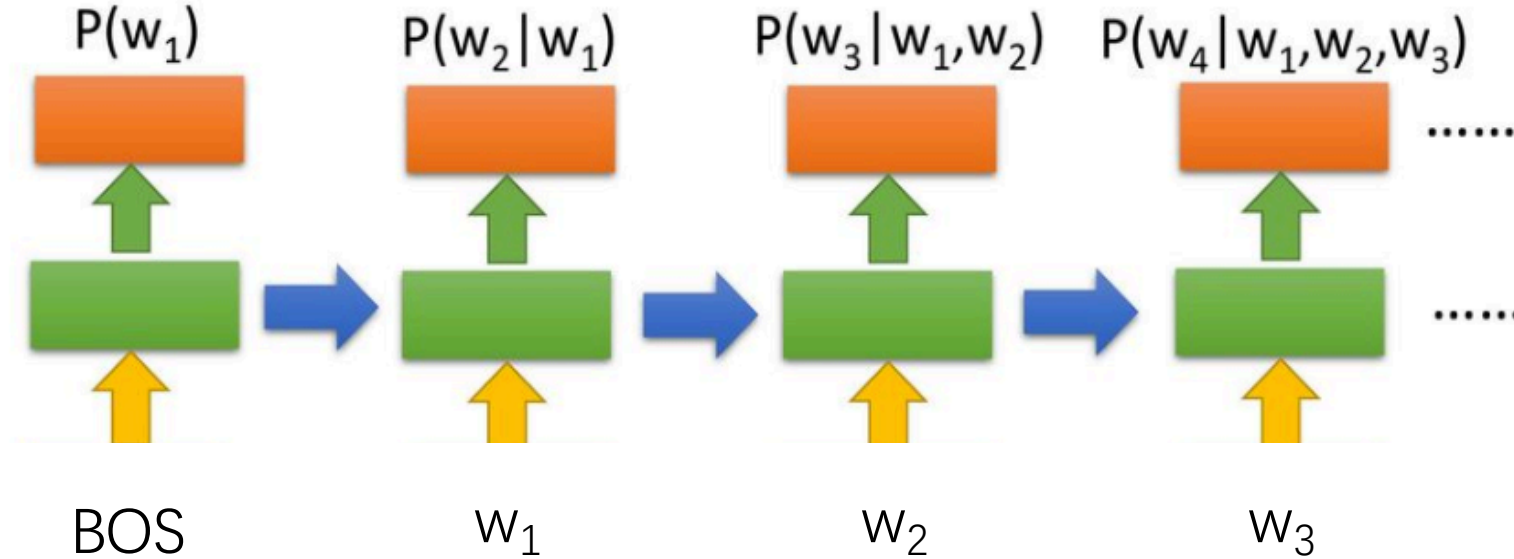
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Background

- Given a grammatical or ungrammatical sentence, grammaticality Evaluation is to assess the grammaticality (or fluency) by scoring
- Most common way is to use language model

Background – Neural Language Model

- The sentence to be evaluated $w_1 w_2 w_3 w_4 \dots$



$$\text{Sentence Perplexity} = e^{-1/N(\sum \log(P_i))}$$

Background - Perplexity

- The lower the Perplexity is, the more likely this sentence occur
- Word frequency has great impact on Perplexity
- Using larger training data usually leads to lower Perplexity

Sample sentence	Perplexity
sees he i often mary ?	7555.2
it seems that it is likely that john will win .	48.9

Perplexity Good for Grammaticality Judgment?

- No

Sample sentence	Perplexity
I travel to London	800.0
I travel to Tuvalu	233.9

GPT2 language model used

- Perplexity favors frequent words, although sentences are equally grammatical

Goals

- An idealized grammaticality evaluator should
 1. Avoid or alleviate the impact of low frequency word (this is especially important for the text contains a number of low-frequency entity)
 2. Grammatical sentence $>$ ungrammatical sentence
 3. ungrammatical sentence with 1 grammar errors $>$ ungrammatical sentence with 4 grammar errors

Eliminating impact of low frequency word by considering POS tags

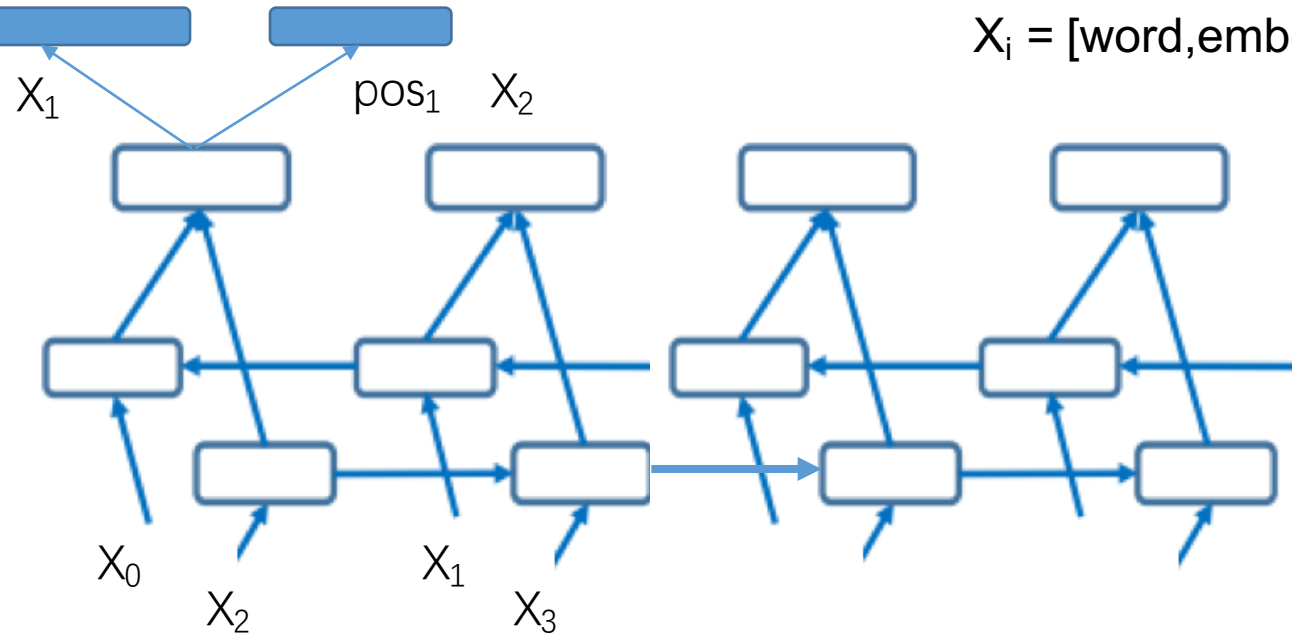
Sample sentence	Perplexity
I travel to London [('I', PRON'), ('travel', VERB'), ('to', ADP'), ('London', PROPN')]	800.0
I travel to Tuvalu [('I', PRON'), ('travel', VERB'), ('to', ADP'), ('Tuvalu', PROPN')]	233.9

POS based Neural Language Model

“two ppl loss terms”

word probability
distribution (softmax)

POS tag probability
distribution (softmax)



$X_i = [\text{word}, \text{embedding}; \text{pos embedding}]$

Training

- Training LM with Gigawords (Agence France-Presse, English Service (afp_eng) scoure, etc.)
- Vocabulary size: ~30,000 subwords
- One-layer unidirectional LSTM language model
- Test Dataset - Corpus of Linguistic Acceptability (CoLA; Warstadt et al., 2018): 1,000 sentences with human judgments (1: grammatical or 0: ungrammatical)

Results

- take (ppl<100) as grammatical prediction and (ppl>100) as ungrammatical prediction

	$f(\mathbf{x})$
LM	0.62
POS-guided LM	0.66

$$f(\mathbf{x}) = \frac{1}{1 + H(\mathbf{x})} \quad \mathbf{D} \in (0, 1]$$

$$H(\mathbf{x}) = -\frac{\sum_{i=1}^{|\mathbf{x}|} \log P(x_i | \mathbf{x}_{<i})}{|\mathbf{x}|} \quad \mathbf{D} \in [0, +\infty)$$

Expectation

- The number of POS tags is less than 50, making pos tag embedding well learned during training
- Model might learn correct collocation of POS tags
- Limitation of this approach:
 - Need pos tagging beforehand
 - Ungrammatical sentence might have wrong pos tagging

Goals

- An idealized grammaticality evaluator should
 1. Avoid or alleviate the impact of low frequency word (this is especially important for the text contains a number of low-frequency entity) ✓
 2. Grammatical sentence > ungrammatical sentence
? Large room for improvement
 3. ungrammatical sentence with 1 grammar errors > ungrammatical sentence with 4 grammar errors

Need category errors

Next

- Testify whether LM is able to detect the grammar errors like
 - Subject-Verb