Surprisal from Large Language Models

AriaRay Brown Julius Steuer

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TaCoS

Goals of this Tutorial

1. Learn to calculate surprisal with our toolkit
2. Learn to use surprisal for psycholinguistic research
3. Learn to calculate surprisal with a language model

Processing Difficulty ~ Surprisal

- Surprisal theory: processing difficulty of a word in context is proportional to its negative log-probability (Hale 2001, Levy 2008)

$$\text{processing difficulty} \approx -\log_2 p(word|context)$$

- If we are interested in the processing difficulty of a word *n* given its context, we calculate its negative log probability given the *k* preceding words

$$\mathbf{surp}(w_n|w_{n-k}, ..., w_{n-1}) = -\log_2 p(w_n|w_{n-k}, ..., w_{n-1})$$

Surprisal from Language Models

- Instead of conditioning on the *n* preceding words, next word predictions are conditioned on the hidden state of transformer models

$$h_{n-1} = f_{\theta_{TF}}(w_{n-k}, ..., w_{n-1})$$

$$p(w_n|h_{n-1}) = softmax(f_{\theta_{LM}}(h_{n-1}))$$

- θ_{LM} can be an n-gram model, LSTM, transformer…

Predictions of Surprisal Theory

- Language model surprisal has been used successfully for reading time prediction (Smith & Levy 2013, Shain et al. 2022)

$$\text{Surp}(\underline{\text{would be changed}} \mid \text{The employees understood that the contract})$$

$$\propto$$

$$\text{RT}(\underline{\text{would be changed}} \mid \text{The employees understood that the contract})$$

- Surprisal theory should be able to **fully explain** reading times.

Reading Time fit with LME Models

- LME = Linear Mixed Effects (model), regression with more than one predictor
- Regression

Reading Time ~ Surprisal

- LME

Reading Time ~ Surprisal(w) + Frequency(w) + Length(w) + 1|w + ...

LME Goodness of Fit

- LMEs are compared via their log-likelihoods (LL)
  - How likely is my data given the fitted LME?
- Compare LME with surprisal as a predictor to a base model
  - LL_surp = Reading Time ~ Surprisal(w) + Frequency(w) + Length(w) + 1|w +
  - LL_base = Reading Time ~ Frequency(w) + Length(w) + 1|w + ...
- Delta of the log-likelihood tells us how much surprisal improved model fit
  - delta_ll = LL_base - LL_surp

Larger is (sometimes) better (in LMs)?

- Wilcox et al. 2020: positive correlation of reading time fit and perplexity

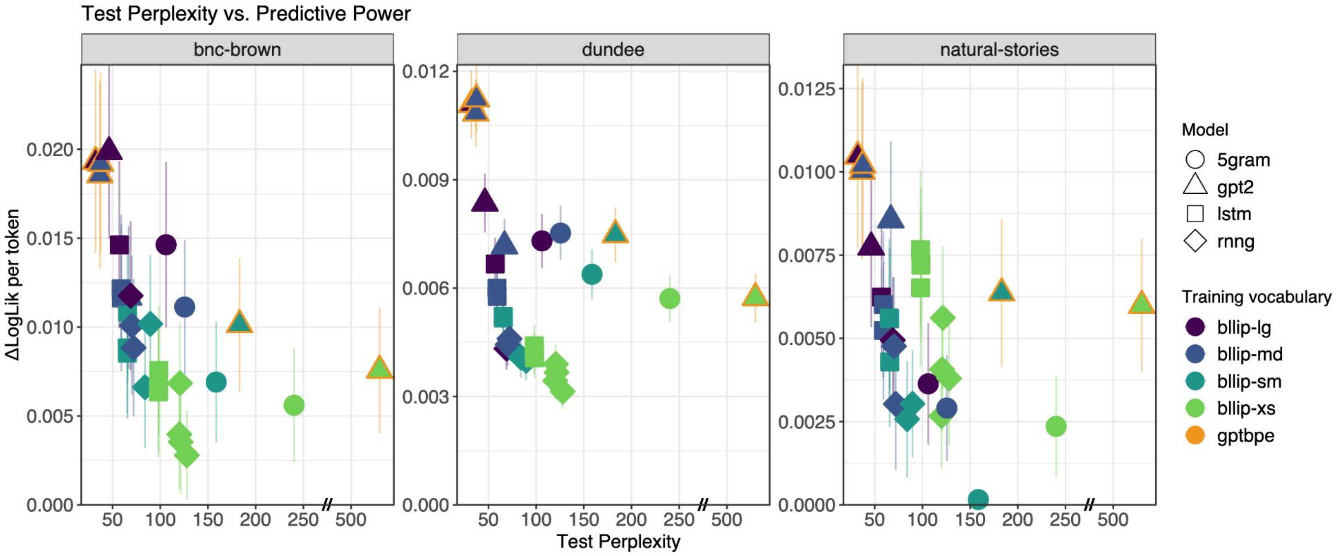
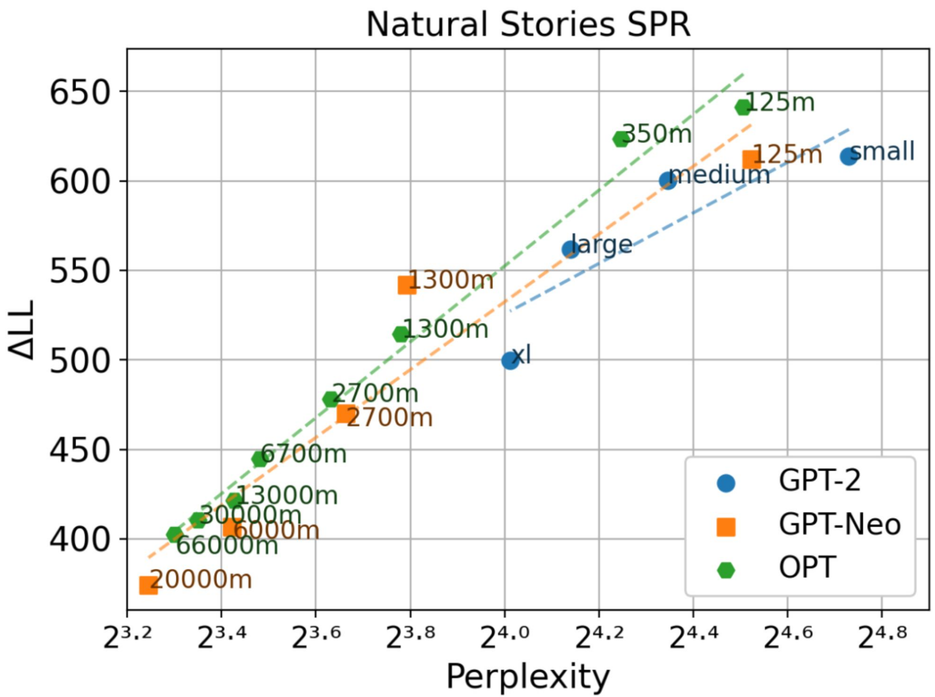


Figure 2: Relationship between predictive power (ΔLogLik) and model perplexity. Error bars are standard errors of by-fold mean ΔLogLik per token, using 10-fold cross validation. As model perplexity decreases, predictive power increases for all test corpora.

Larger is not always better (in LMs)!

- Oh & Schuler 2023
- LME(Reading Time ~ Surprisal)
- Inverse scaling of perplexity (model size) & reading time fit
- Oh & Schuler 2024: larger models memorize infrequent items -> underestimate surprisal



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