

Frequency Explains the Inverse Correlation of Large Language Models' Size, Training Data Amount, and Surprisal's Fit to Reading Times

Byung-Doh Oh¹

¹The Ohio State University

oh.531@osu.edu

Shisen Yue²

²Shanghai Jiao Tong University

lyw520@sjtu.edu.cn

William Schuler¹

schuler.77@osu.edu

Abstract

Recent studies have shown that as Transformer-based language models become larger and are trained on very large amounts of data, the fit of their surprisal estimates to naturalistic human reading times degrades. The current work presents a series of analyses showing that word frequency is a key explanatory factor underlying these two trends. First, residual errors from four language model families on four corpora show that the inverse correlation between model size and fit to reading times is the strongest on the subset of least frequent words, which is driven by excessively accurate predictions of larger model variants. Additionally, training dynamics reveal that during later training steps, all model variants learn to predict rare words and that larger model variants do so more accurately, which explains the detrimental effect of both training data amount and model size on fit to reading times. Finally, a feature attribution analysis demonstrates that larger model variants are able to accurately predict rare words based on both an effectively longer context window size as well as stronger local associations compared to smaller model variants. Taken together, these results indicate that Transformer-based language models' surprisal estimates diverge from human-like expectations due to the superhumanly complex associations they learn for predicting rare words.

1 Introduction

The predictability of linguistic material in its context has been shown to be an important factor of real-time processing difficulty (Hale, 2001; Levy, 2008), with a large body of empirical work showing surprisal (Shannon, 1948) to be a strong predictor of relevant behavioral and neural measures (Demberg and Keller, 2008; Smith and Levy, 2013; Hale et al., 2018; Shain et al., 2020, *i.a.*). Therefore, a core research goal of expectation-based theories of sentence processing has been to characterize the

latent probability distribution of the human comprehender. Language models (LMs) that define a conditional probability distribution are helpful for exploring these questions, as they can be trained to embody different predictive processes and yield concrete surprisal estimates that can be evaluated against measures of processing difficulty.

Recent work using surprisal estimates from Transformer-based LMs has revealed a strong inverse correlation between the size of LMs and the fit of their surprisal estimates to naturalistic human reading times, where larger models yield surprisal estimates that are less predictive of reading times (Oh et al., 2022; Oh and Schuler, 2023b; Shain et al., 2022; de Varda and Marelli, 2023). Large amounts of training data have also been shown to play a detrimental role, with fit to reading times starting to degrade after LMs see about two billion tokens (Oh and Schuler, 2023a). This robust inverse correlation is meaningful, as it shows that increasingly larger LMs are less appropriate as models of human cognition, and that human sentence processing is not driven by the predictions LMs make with more model parameters and training data. While open-class words like nouns and adjectives have been identified as driving the adverse effect of model size (Oh and Schuler, 2023b), how model size and the training data interact during LM training to give rise to such systematic divergence from human-like expectations remains unclear.

Studies on the scaling behavior of large LMs have recently shown that larger models learn examples faster by increasing their probabilities to a greater extent given the same amount of exposure (Tirumala et al., 2022). However, during early training stages, models of all sizes exhibit similar next-token predictions by learning to accurately predict frequent function words (Xia et al., 2023). This suggests that the difference in surprisal estimates as a function of model size will be modulated by frequency and will increase as models see larger

amounts of training data.

Based on these observations, this work presents a series of analyses showing that word frequency is a key explanatory factor of the inverse correlation between model size, training data amount, and surprisal’s fit to reading times. First, residual errors from four LM families on four corpora show that the inverse correlation between model size and fit to reading times is the strongest on the subset of least frequent words, which is driven by excessively accurate predictions of larger model variants. Moreover, training dynamics reveal that all model variants learn to predict rare words during later training steps and larger model variants do so more accurately, which explains the detrimental effect of both training data amount and model size on fit to reading times. Finally, a feature attribution analysis demonstrates that larger model variants predict rare words more accurately compared to smaller model variants based on both an effectively longer context window and stronger local associations. These results provide evidence that Transformer-based LMs’ surprisal estimates diverge from human-like expectations due to the superhumanly complex associations they learn for predicting rare words.

2 Experiment 1: Effect of Frequency on Strength of Inverse Correlation

The first experiment examines the influence of word frequency on the strength of the inverse correlation between model size and fit to reading times by evaluating surprisal estimates from four LM families on four corpora of naturalistic reading times collected through both self-paced reading and eye-tracking paradigms.

2.1 Response Data

The reading times analyzed in this experiment come from the Natural Stories Corpus (Futrell et al., 2021), the Dundee Corpus (Kennedy et al., 2003), the Ghent Eye-Tracking Corpus (GECO; Cop et al., 2017), and the Provo Corpus (Luke and Christianson, 2018). The Natural Stories Corpus contains self-paced reading times from 181 subjects that read 10 naturalistic English stories consisting a total of 10,245 words. The Dundee Corpus contains eye-gaze durations from 10 subjects that read 67 English newspaper editorials consisting a total of 51,501 words. The GECO contains eye-gaze durations from 14 monolingual subjects that read the English version of the novel *The Mysterious Af-*

fair at Styles (Christie, 1920), which consists of 13 chapters and 56,441 words. The Provo Corpus contains eye-gaze durations from 84 subjects that read 55 short English passages consisting a total of 2,746 words that range from news articles, science magazines, and works of fiction.

For the Natural Stories Corpus, data points were filtered to exclude those for sentence-initial and final words, those from subjects who answered fewer than four comprehension questions correctly, and those shorter than 100 ms or longer than 3000 ms, which resulted in 384,905 observations in the exploratory set. For the three eye-tracking corpora, data points were filtered to remove those for unfixated words, words following saccades longer than four words, and words at starts and ends of sentences, screens, documents, and lines. This resulted in a total of 98,115, 144,850, and 52,960 observations in the exploratory sets of the Dundee Corpus, GECO, and the Provo Corpus respectively.¹ All observations were log-transformed before regression modeling, following previous work (e.g. Oh and Schuler, 2023b).²

2.2 Predictors

This experiment evaluates surprisal estimates from variants of four LM families, namely the GPT-2 (Radford et al., 2019), GPT-Neo (Black et al., 2021, 2022; Wang and Komatsuzaki, 2021), OPT (Zhang et al., 2022), and Pythia (Biderman et al., 2023) families. All of these LMs are autoregressive Transformer-based models whose variants differ primarily in their size. The hyperparameters of all examined variants are outlined in Appendix A.

Each chapter or article of the four corpora was tokenized using each LM’s respective byte-pair encoding (BPE; Sennrich et al., 2016) tokenizer and provided to all variants to calculate surprisal estimates, i.e. $-\log_2 P(w_{i+1} | w_{1..i})$. In cases where each chapter or article did not fit completely into one context window, surprisal estimates for the remaining tokens were calculated by conditioning on the second half of the previous context window.

In addition to these surprisal predictors, a set of baseline predictors that capture low-level pro-

¹The exploratory set of each corpus consists of roughly 50% of all data points based on the sum of subject ID and sentence number. The held-out set is reserved for statistical significance testing and not analyzed in this work.

²The log-transform implicitly assumes a superlinear linking function between surprisal and reading times, which has been shown to produce tighter fits for surprisal from larger LM variants (Shain et al., 2022; Hoover et al., 2023).

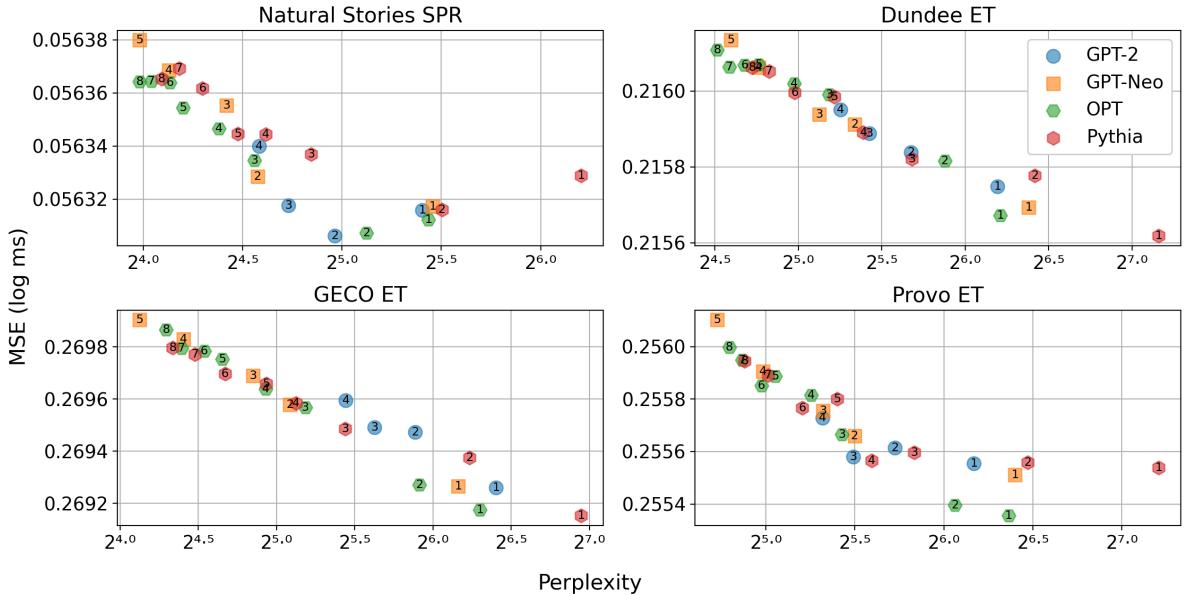


Figure 1: Corpus-level perplexity measures from each GPT-2, GPT-Neo, OPT, and Pythia model variant, and mean squared errors of regression models that include each surprisal predictor on the four corpora of reading times. The ordered labels represent variants of different sizes, where ‘1’ represents the smallest variant of each LM family.

cessing was also included in all regression models. These predictors are word length in characters, index of word position within each sentence, unigram surprisal (both self-paced reading and eye-tracking corpora), as well as saccade length and whether the previous word was fixated (eye-tracking corpora only). Unigram surprisal was estimated using counts of ~ 33 billion pre-tokenized tokens from the Pile (Gao et al., 2020), which is a collection of English language datasets.³ All predictors were standardized by centering and scaling before model fitting, and ‘spillover’ versions of predictors were not included in the regression models to avoid convergence issues and simplify the analyses.

2.3 Regression Modeling

Subsequently, a set of linear mixed-effects (LME) models that contain one surprisal predictor and the baseline predictors outlined in Section 2.2 were fit to self-paced reading times of the Natural Stories Corpus and go-past durations⁴ of the three eye-tracking corpora using lme4 (Bates et al., 2015). All LME models included by-subject random slopes for all fixed effects and random inter-

³Whenever a word consisted of multiple subword tokens, token-level unigram surprisal was summed to calculate the word-level unigram surprisal. Code for calculating LM surprisal and unigram surprisal is available at https://github.com/byungdoh/l1m_surprisal.

⁴Go-past durations were analyzed in this work as regressive eye movements are thought to reflect additional processing difficulty that is incurred by the current word.

cepts for each subject. Additionally, random intercepts were included for each subject-sentence interaction for self-paced reading times collected from 181 subjects, and random intercepts were included for each sentence for eye-gaze durations collected from smaller subject pools. After the regression models were fit, their predictions were subtracted from the target reading times to calculate the residual errors for each regression model.

To examine the effect of word frequency on the strength of inverse correlation between model size and fit to reading times, the data points in each corpus were divided into quintiles according to unigram log-probabilities of the target word. Subsequently, the mean squared errors (MSEs) from each regression model were calculated on each quintile. The corpus-level perplexity of each model variant is also calculated and reported as a proxy for model size, based on a preliminary analysis showing very little difference in surprisal values among very large LM variants.

2.4 Results

The results in Figure 1 show that regression models with surprisal predictors from smaller model variants generally had lower MSEs across the four LM families on all four corpora.⁵ This replicates

⁵The best-fitting lines between log perplexity and MSE had a slope significantly lower than 0 at $p < 0.05$ level by a one-tailed t -test on all four corpora.

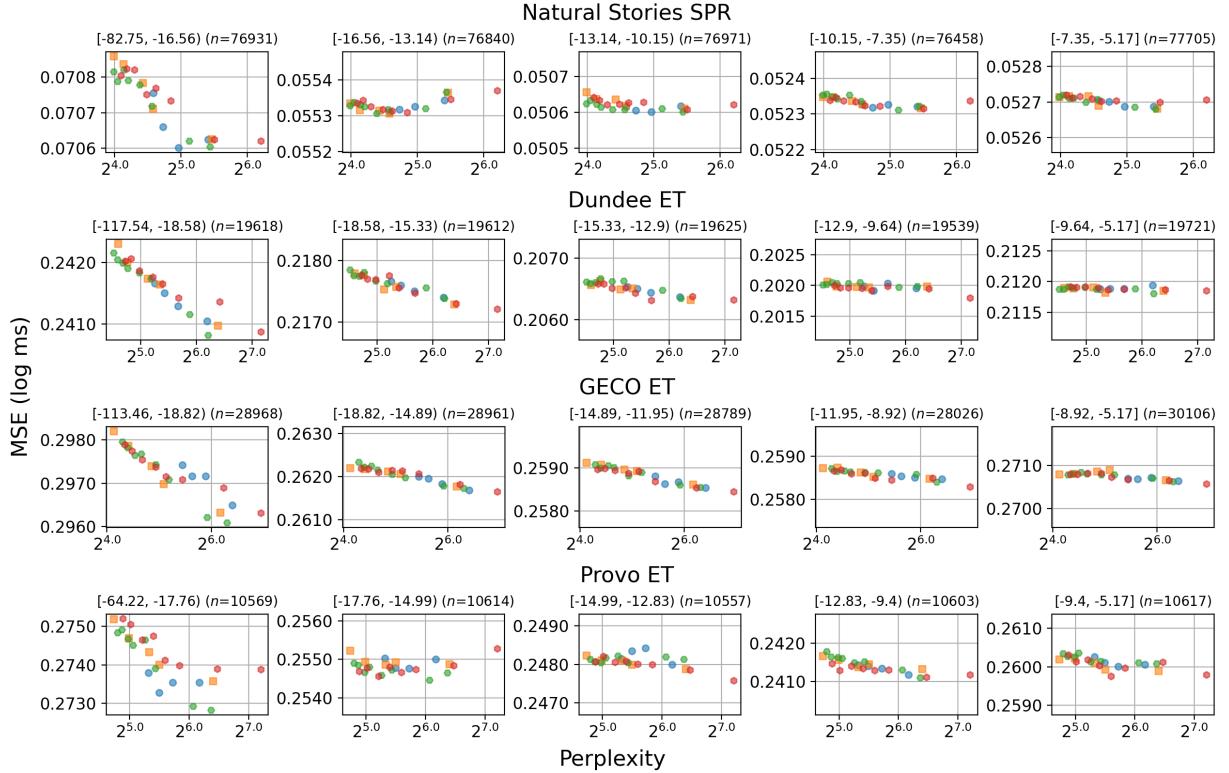


Figure 2: Corpus-level perplexity measures from each GPT-2, GPT-Neo, OPT, and Pythia model variant, and mean squared errors of regression models that include each surprisal predictor on the four corpora of reading times. The columns of subplots represent the five quintiles defined by unigram log-probabilities.

previous results reporting the inverse correlation between model size and fit to reading times (Oh and Schuler, 2023b) and provides further empirical support for the effect.

The MSEs partitioned according to unigram probabilities in Figure 2 reveal that this corpus-level effect is primarily driven by the subset of least frequent words. On all four corpora, the negative slope between log perplexity and MSE is the steepest on the first quintile, which is significantly lower than the other subsets at $p < 0.05$ level by a permutation test that shuffles the quintile membership of the word. The MSEs of regression models are also the largest on the first quintile on all four corpora, which suggests that the subset of rare words is where surprisal estimates from Transformer-based LMs diverge from human reading times the most.

A breakdown of the average surprisal values and sum of squared errors⁶ (SSEs) from underpredicted and overpredicted data points of each quintile in Figure 3 shows that larger model variants make especially accurate predictions on the subset of least

frequent words compared to their smaller counterparts, where the difference in average surprisal is the biggest between model variants. While more severe underpredictions of reading times are mostly responsible for the overall trend on this subset, the overpredictions do not appear to cancel out the trend, as is the case on other quintiles.

In contrast, more severe overpredictions of reading times seem to drive the overall trend on the subsets of more frequent words. This is likely due more to the estimated regression coefficients rather than the surprisal predictors, the difference in which between model variants is much smaller compared to other subsets. As surprisal predictors from larger LM variants are smaller in magnitude, the regression models assign them higher coefficients to predict the same target reading times, which results in a systematic overprediction given surprisal predictors of similar magnitudes.

3 Experiment 2: Effect of Training Data Amount on Fit to Reading Times

The previous experiment showed that the excessively accurate predictions of larger variants on the subset of least frequent words strongly drive the

⁶SSEs are presented instead of MSEs as each regression model had different numbers of underpredicted and overpredicted data points, which can distort the MSEs and obscure the overall trend of mispredictions.

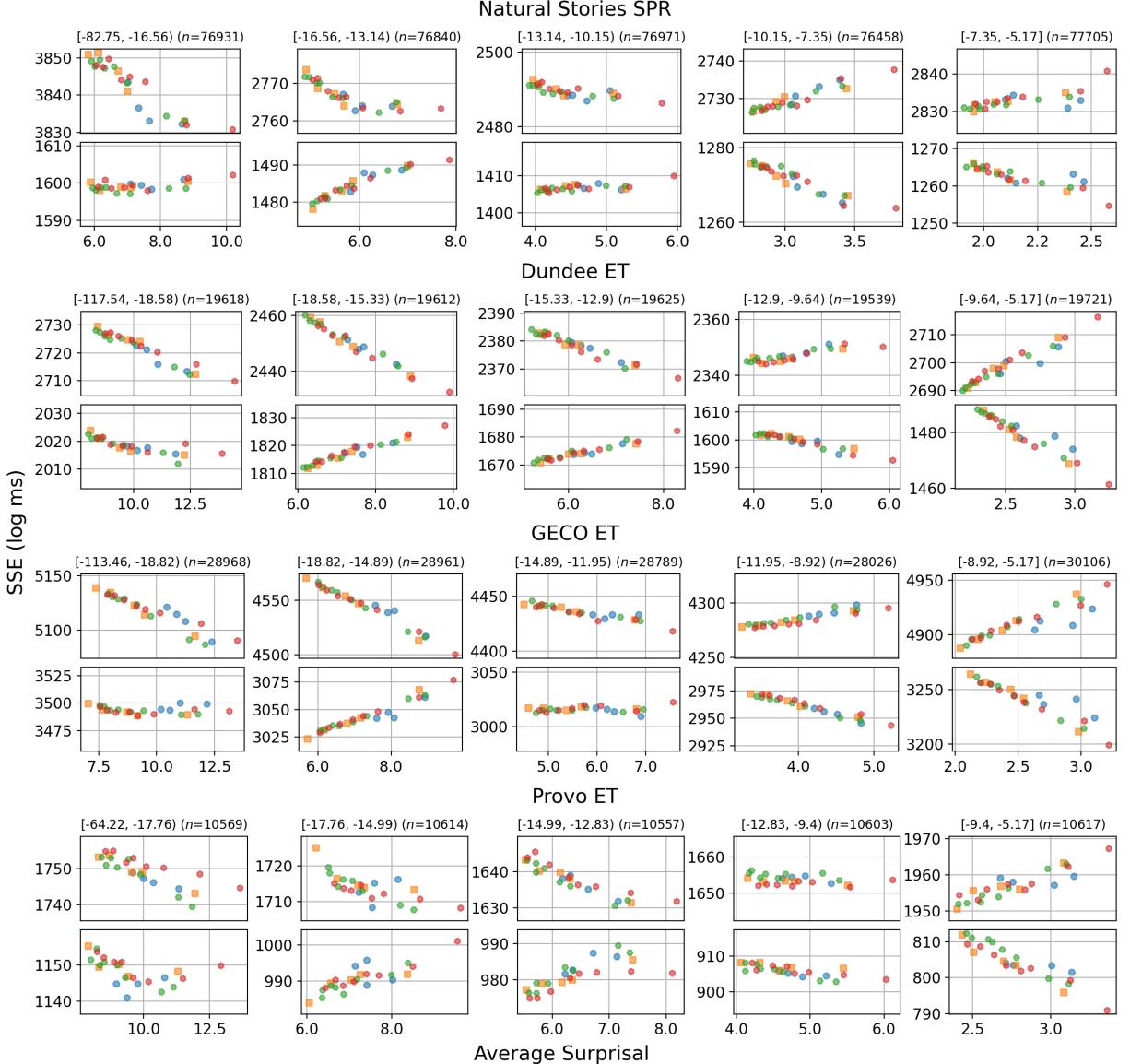


Figure 3: Average surprisal values from each GPT-2, GPT-Neo, OPT, and Pythia model variant, and sum of squared errors of regression models that include each surprisal predictor on the four corpora of reading times. The columns of subplots represent the five quintiles defined by unigram log-probabilities. The top and bottom subplots of each row represent values from underpredicted and overpredicted data points, respectively.

inverse correlation between model size and fit to human reading times. The second experiment examines the training dynamics of Pythia model variants to study the influence of training data amount and model size on the ability of LMs to predict rare words, as well as the resulting fit of their surprisal estimates to human reading times.

3.1 Procedures

Among the four LM families examined in the previous experiment, the Pythia models are the only LMs that have publicly available checkpoints at various points during training. These model variants were trained on batches of 1,024 examples with

2,048 tokens for a total of 143,000 training steps (~ 300 billion tokens). Intermediate checkpoints that were saved during early training stages and after every 1,000 steps are publicly available.

To examine the training dynamics of these eight variants, surprisal estimates were calculated after $\{0, 128, 256, 512, 1000, 2000, 4000, 8000, 143000\}$ training steps on the four corpora of reading times.⁷ Subsequently, following identical regression mod-

⁷The Pythia variants evaluated in Experiment 1 are those that were fully trained for all 143,000 training steps. These steps were selected based on previous work that show a peak in fit to human reading times at around 1,000 training steps, and relatively little change after step 8,000 onwards for the Pythia models (Oh and Schuler, 2023a).

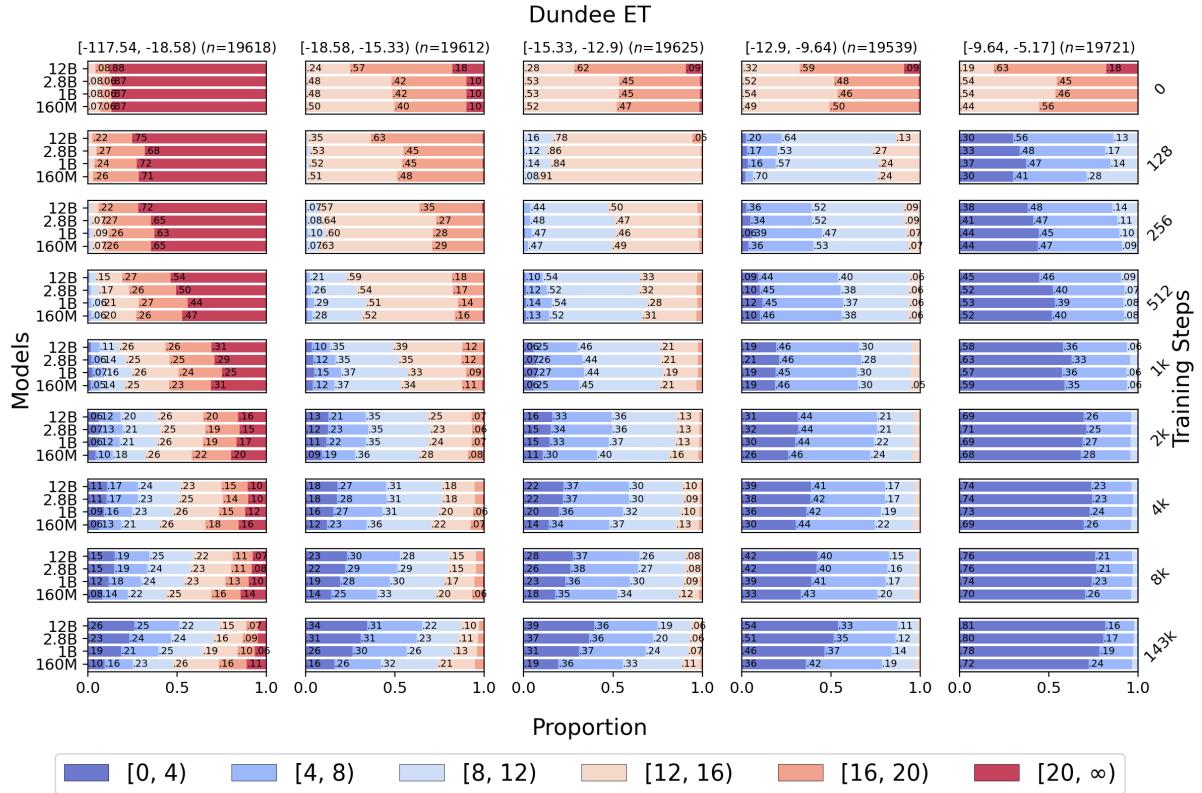


Figure 4: Proportion of surprisal values from select Pythia model variants on each quintile of the Dundee Corpus as a function of training steps. Proportions that are greater than .05 are annotated.

eling procedures as Experiment 1, LME models were fit to reading times and their residual errors were calculated. Finally, the data points in each corpus were divided into quintiles according to unigram log-probabilities of the target word to examine the change in surprisal values and residual errors as a function of word frequency through the course of LM training.

3.2 Results

The surprisal values in Figure 4⁸ show that at initialization (i.e. after 0 training steps), surprisal values are the highest on the first quintile, as they are tokenized into multiple tokens by the BPE tokenizer. During early training of up to 256 steps, all model variants primarily learn to predict frequent tokens, resulting in a large decrease in surprisal values on the fifth quintile. As training continues, all model variants begin to learn to predict less frequent tokens, resulting in a consistent decrease in surprisal values on the lower quintiles. Most notably, there seems to be no strong trend in surprisal values as a

function of model size up until 1,000 training steps.

In contrast, from training step 2,000 onward, the larger variants begin to yield lower surprisal values than their smaller counterparts, which suggests that the learning by larger variants actively continues while that by smaller variants begins to slow down. By the end of training, this results in a general trend where the difference in surprisal values between model variants gets progressively bigger on the lower quintiles, as was demonstrated in Figure 3.

The SSEs from regression models containing these surprisal predictors in Figure 5⁹ show that learning to predict rare tokens initially improves fit to reading times up to training step 1,000 by mostly improving the prediction of reading times of these words. However, as the model variants see larger amounts of data and continue learning to predict rare tokens, the squared errors on these reading times begin to increase. As larger model variants learn to do so more accurately, the increase in squared errors is also steeper for the corresponding regression models. This demonstrates that both training data amount and model size help the accu-

⁸Data from select Pythia model variants on the Dundee Corpus is presented due to space constraints. Refer to Appendix B for comparable figures with all eight model variants on all four corpora.

⁹Refer to Appendix C for comparable figures with all eight model variants on all four corpora.

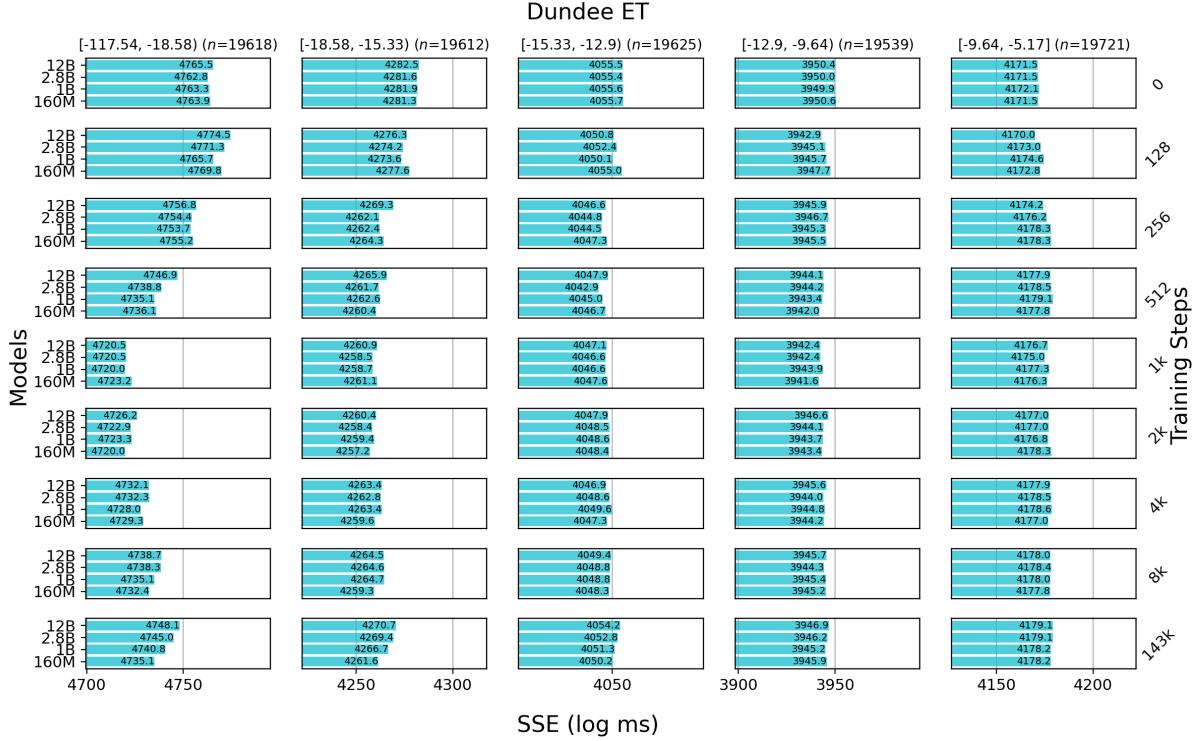


Figure 5: SSEs from regression models containing surprisal predictors from select Pythia model variants on each quintile of the Dundee Corpus as a function of training steps. The columns of subplots share the scale but not the range of the x-axis for visual clarity.

rate prediction of low-frequency words, which in turn has a detrimental effect on fit to reading times.

4 Follow-up Analysis: What Enables Larger Models to Predict Rare Words?

The previous experiment showed that as LM variants are trained on large amounts of data, all variants learn to predict rare words during later training steps. However, larger variants are able to do so more accurately, thereby ultimately resulting in surprisal estimates that are poorer predictors of human reading times. The goal of this follow-up analysis is to provide a mechanistic explanation underlying the behavior of larger LM variants identified through the main experiments, by elucidating how the increase in model size enables LMs to make more accurate predictions of rare words.

Although the predictions of Transformer-based language models are opaque and difficult to interpret, one possible explanation for this phenomenon is that the larger variants have a longer ‘effective’ context window size than smaller variants. In other words, although all Transformers theoretically have veridical access to the context, the smaller variants may not be able to learn associations to early material in the context due to their limited capacity. This

follow-up analysis gauges the contribution of early and recent context tokens using a feature attribution method to examine what enables larger model variants to predict rare words more accurately than their smaller counterparts.

4.1 Procedures

The feature attribution method adopted for this analysis is based on limiting the LM’s context to the most recent n tokens (Kuribayashi et al., 2022), which can also be viewed as an ablation of the earlier context tokens (*occlusion*; Zeiler and Fergus, 2014). This method has the advantages that it quantifies the contribution of context tokens in terms of interpretable probabilities (cf. gradient-based methods) and does not suffer from potential out-of-distribution issues (Hooker et al., 2019) as it keeps contiguous n -grams intact and does not arbitrarily alter their vector representations.

Surprisal estimates from the eight fully-trained Pythia variants were calculated on the quintile of least frequent words of the four reading time corpora by conditioning on the most recent {49, 24, 9} context tokens. The resulting surprisal values were compared to those calculated by conditioning on the full context to examine the impact of early

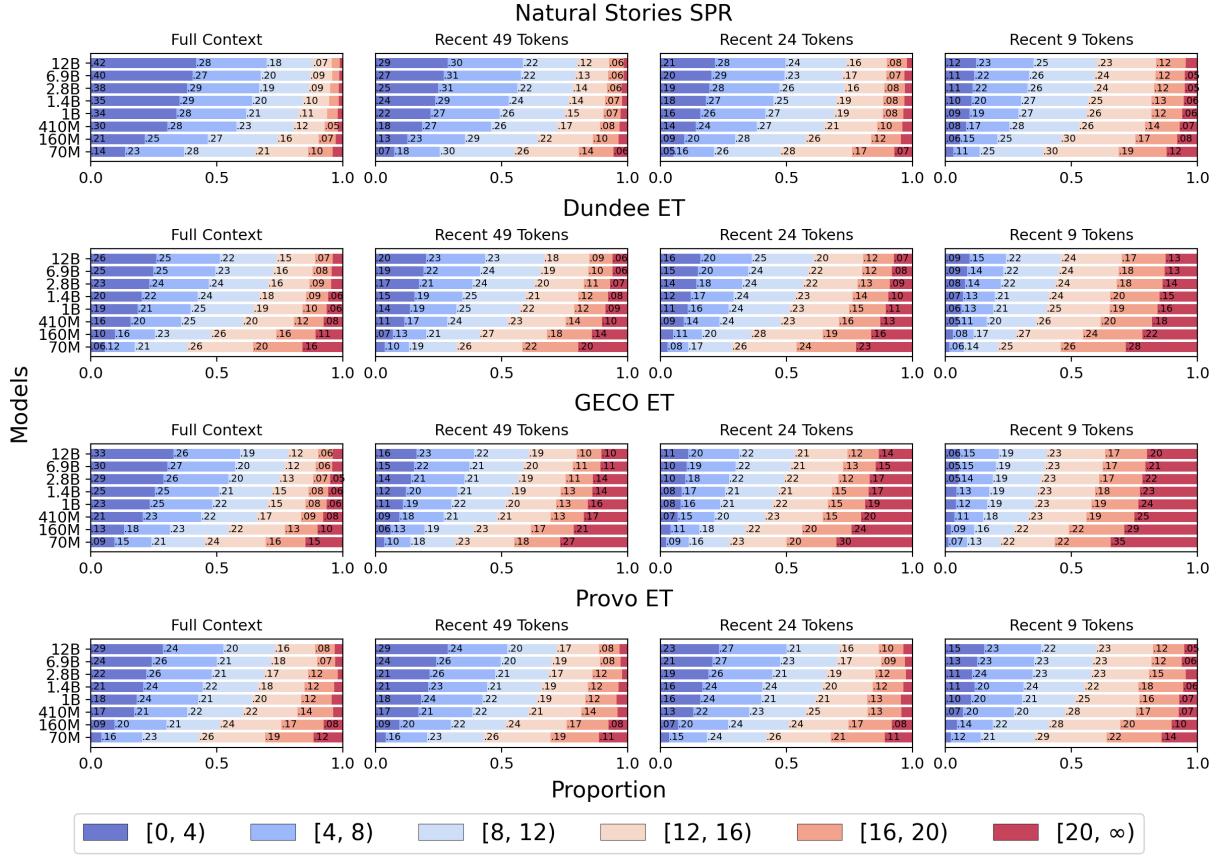


Figure 6: Proportion of surprisal values from Pythia model variants on the quintile of least frequent words of the four corpora of reading times as a function of context window size. Proportions that are greater than .05 are annotated.

and recent context tokens. If the early material in context is crucial for a model variant to predict rare tokens, larger increases in their surprisal values will be observed when the context window is limited.

4.2 Results

The results in Figure 6 show that on all four corpora, surprisal values from all variants progressively increase as the context window becomes more limited. This increase seems to be modulated by model size, where larger variants demonstrate larger degrees of increase as a result of limiting the context window. This suggests that larger variants have learned stronger associations with early context tokens and therefore have effectively longer context windows for predicting rare tokens.

However, surprisal values calculated under the most restrictive nine-token condition show that larger model variants are still able to make more accurate predictions than their smaller counterparts even when the context is very limited. Taken together, these results indicate that larger model variants are able to predict rare words more accurately based on both an effectively longer context window

as well as stronger local associations.

5 Discussion

This work presents word frequency as a unified explanation for the degradation in fit of surprisal estimates to naturalistic human reading times as a function of LM size and training data amount observed in recent studies. First, evaluation of model variants from four LM families on four corpora of reading times shows that the inverse correlation between model size and fit to reading times is the strongest on the subset of least frequent words. This is due to the larger model variants’ disproportionately accurate predictions on this subset, where the target reading times are generally longer. These findings are consistent with those from the analyses of Oh and Schuler (2023b), who found that more severe underpredictions of reading times of open-class words like nouns and adjectives most strongly drive the trend between model size and regression model fit. Word frequency provides a more general and parsimonious account of the trend on the entire corpus, as well as a complementary view of the phenomenon.

The training dynamics of LMs also show a strong interaction between frequency and model size through the course of training. More specifically, model variants of all sizes learn to accurately predict frequent tokens and also show little difference in surprisal values during early training steps. However, as they continue to see large amounts of data, they start learning to predict rare tokens accurately. It is at this later point in training where the difference between model variants begins to manifest, with larger variants learning to make more accurate predictions of these rare tokens. These trends are consistent with prior work on the scaling behavior of large LMs (Tirumala et al., 2022; Xia et al., 2023), as well as observations that neural LMs first approximate unigram and then bigram probabilities during early training (Chang and Bergen, 2022; Chang et al., 2023).

Residual errors from regression models containing surprisal estimates at intermediate points during LM training show that learning to predict rare tokens initially improves fit to reading times by primarily improving the prediction of reading times of these rare words. Nonetheless, as the model variants continue learning to predict rare tokens, the errors on these reading times begin to increase. Since larger model variants learn to predict rare tokens more accurately, the regression models containing their surprisal estimates also exhibit a steeper increase in errors. This illustrates the detrimental effect of training data amount and model size on fit to reading times, and also explains Oh and Schuler’s (2023a) observation of the peak in fit to reading times at around two billion training tokens.

The follow-up feature attribution analysis that ablates the contribution of early context tokens suggests that larger model variants utilize both an effectively longer context window and stronger local associations to predict rare tokens more accurately than their smaller counterparts. Limiting the number of tokens in the context window weakens these associations for predicting rare words, which is most likely the reason why this improves the fit of LM surprisal to reading times, as demonstrated by Kuribayashi et al. (2022).

Taken together, these results indicate that both model size and large amounts of training data allow Transformer-based LMs to learn superhumanly complex associations for predicting rare words, which in turn adversely affects fit to human reading times. In other words, surprisal from model variants that are smaller and trained on less data yield

a better fit to naturalistic reading times because they implicitly capture word frequency. This has important implications for research into whether frequency effects are dissociable from predictability effects in naturalistic reading (e.g. Goodkind and Bicknell, 2021; Shain, 2019, 2023). One possible interpretation of the current results is that they provide support for a strong and dissociable frequency effect, as the subset of rare words is where LM surprisal estimates diverge most from naturalistic reading times as a whole. However, they may also indicate that the excessive number of parameters and training data result in surprisal estimates that have washed out frequency effects which could have been explained by predictability.

An interesting direction for future work is extending the current analyses to data collected in other languages (e.g. Kuribayashi et al., 2021; de Varda and Marelli, 2023; Wilcox et al., 2023). Based on the training dynamics of LMs observed in this work, to the extent that they are of sufficient sizes and are trained on large amounts of data, the explanation based on word frequency is expected to robustly generalize to data from other languages.

6 Conclusion

This work proposes word frequency as an explanation for the inverse correlation observed between Transformer-based LMs’ size, training data amount, and surprisal’s fit to human reading times. Four LM families on four corpora show the strongest inverse correlation between model size and fit to reading times on the least frequent words, which is driven by the more accurate predictions of the larger variants. Training dynamics reveal that all variants learn to predict rare words with large amounts of data and larger variants do so more accurately, which explains the detrimental effect of both model size and training data amount. These results indicate that the superhumanly complex associations for predicting rare words make Transformer-based LMs’ surprisal estimates diverge from human-like expectations.

Acknowledgments

We thank the ARR reviewers and the area chair for their helpful comments. This work was supported by the National Science Foundation grant #1816891. All views expressed are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Limitations

The explanation for the dissociation between surprisal estimates from Transformer-based language models and real-time comprehension difficulty developed in this work is based on language model variants trained on English text and data from subjects that are native speakers of English. Therefore, the proposed explanation may not generalize to other languages. Other possible limitations include the assumption of linear effects and the lack of spillover predictors in regression modeling.

Ethics Statement

This work used data collected as part of previously published research (Futrell et al., 2021; Kennedy et al., 2003; Cop et al., 2017; Luke and Christianson, 2018). Readers are referred to the respective publications for more information on the data collection and validation procedures. As this work focuses on studying the connection between conditional probabilities of language models and human sentence processing, its potential negative impacts on society appear to be minimal.

References

- Douglas Bates, Martin Mächler, Ben Bolker, and Steve Walker. 2015. [Fitting linear mixed-effects models using lme4](#). *Journal of Statistical Software*, 67(1):1–48.
- Stella Biderman, Hailey Schoelkopf, Quentin Gregory Anthony, Herbie Bradley, Kyle O’Brien, Eric Hallahan, Mohammad Aflah Khan, Shivanshu Purohit, USVSN Sai Prashanth, Edward Raff, Aviya Skowron, Lintang Sutawika, and Oskar van der Wal. 2023. [Pythia: A suite for analyzing large language models across training and scaling](#). In *Proceedings of the 40th International Conference on Machine Learning*, volume 202, pages 2397–2430.
- Sid Black, Stella Biderman, Eric Hallahan, Quentin Anthony, Leo Gao, Laurence Golding, Horace He, Connor Leahy, Kyle McDonell, Jason Phang, Michael Pieler, USVSN Sai Prashanth, Shivanshu Purohit, Laria Reynolds, Jonathan Tow, Ben Wang, and Samuel Weinbach. 2022. [GPT-NeoX-20B: An open-source autoregressive language model](#). In *Proceedings of BigScience Episode #5 – Workshop on Challenges & Perspectives in Creating Large Language Models*, pages 95–136.
- Sid Black, Leo Gao, Phil Wang, Connor Leahy, and Stella Biderman. 2021. [GPT-Neo: Large scale autoregressive language modeling with Mesh-Tensorflow](#). *Zenodo*.
- Tyler A. Chang and Benjamin K. Bergen. 2022. [Word acquisition in neural language models](#). *Transactions of the Association for Computational Linguistics*, 10:1–16.
- Tyler A. Chang, Zhuowen Tu, and Benjamin K. Bergen. 2023. [Characterizing learning curves during language model pre-training: Learning, forgetting, and stability](#). *arXiv preprint*, arXiv:2308.15419.
- Agatha Christie. 1920. [The Mysterious Affair at Styles](#). John Lane. Retrieved from Project Gutenberg.
- Uschi Cop, Nicolas Dirix, Denis Drieghe, and Wouter Duyck. 2017. [Presenting GECO: An eyetracking corpus of monolingual and bilingual sentence reading](#). *Behavior Research Methods*, 49(2):602–615.
- Andrea de Varda and Marco Marelli. 2023. [Scaling in cognitive modelling: A multilingual approach to human reading times](#). In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics*, pages 139–149.
- Vera Demberg and Frank Keller. 2008. [Data from eye-tracking corpora as evidence for theories of syntactic processing complexity](#). *Cognition*, 109(2):193–210.
- Richard Futrell, Edward Gibson, Harry J. Tily, Idan Blank, Anastasia Vishnevetsky, Steven Piantadosi, and Evelina Fedorenko. 2021. [The Natural Stories corpus: A reading-time corpus of English texts containing rare syntactic constructions](#). *Language Resources and Evaluation*, 55:63–77.
- Leo Gao, Stella Biderman, Sid Black, Laurence Golding, Travis Hoppe, Charles Foster, Jason Phang, Horace He, Anish Thite, Noa Nabeshima, Shawn Presser, and Connor Leahy. 2020. [The Pile: An 800GB dataset of diverse text for language modeling](#). *arXiv preprint*, arXiv:2101.00027.
- Adam Goodkind and Klinton Bicknell. 2021. [Local word statistics affect reading times independently of surprisal](#). *arXiv preprint*, arXiv:2103.04469v2.
- John Hale. 2001. [A probabilistic Earley parser as a psycholinguistic model](#). In *Proceedings of the Second Meeting of the North American Chapter of the Association for Computational Linguistics on Language Technologies*, pages 1–8.
- John Hale, Chris Dyer, Adhiguna Kuncoro, and Jonathan Brennan. 2018. [Finding syntax in human encephalography with beam search](#). In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics*, pages 2727–2736.
- Sara Hooker, Dumitru Erhan, Pieter-Jan Kindermans, and Been Kim. 2019. [A benchmark for interpretability methods in deep neural networks](#). In *Advances in Neural Information Processing Systems*, volume 32.
- Jacob Louis Hoover, Morgan Sonderegger, Steven T. Piantadosi, and Timothy J. O’Donnell. 2023. [The plausibility of sampling as an algorithmic theory of sentence processing](#). *Open Mind*, 7:350–391.

- Alan Kennedy, Robin Hill, and Joël Pynte. 2003. The Dundee Corpus. In *Proceedings of the 12th European Conference on Eye Movement*.
- Tatsuki Kurabayashi, Yohei Oseki, Ana Brassard, and Kentaro Inui. 2022. Context limitations make neural language models more human-like. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 10421–10436.
- Tatsuki Kurabayashi, Yohei Oseki, Takumi Ito, Ryo Yoshida, Masayuki Asahara, and Kentaro Inui. 2021. Lower perplexity is not always human-like. In *Proceedings of the Joint Conference of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing*, pages 5203–5217.
- Roger Levy. 2008. Expectation-based syntactic comprehension. *Cognition*, 106(3):1126–1177.
- Steven G. Luke and Kiel Christianson. 2018. The Provo Corpus: A large eye-tracking corpus with predictability norms. *Behavior Research Methods*, 50(2):826–833.
- Byung-Doh Oh, Christian Clark, and William Schuler. 2022. Comparison of structural parsers and neural language models as surprisal estimators. *Frontiers in Artificial Intelligence*, 5:777963.
- Byung-Doh Oh and William Schuler. 2023a. Transformer-based language model surprisal predicts human reading times best with about two billion training tokens. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 1915–1921.
- Byung-Doh Oh and William Schuler. 2023b. Why does surprisal from larger Transformer-based language models provide a poorer fit to human reading times? *Transactions of the Association for Computational Linguistics*, 11:336–350.
- Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. *OpenAI Technical Report*.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics*, pages 1715–1725.
- Cory Shain. 2019. A large-scale study of the effects of word frequency and predictability in naturalistic reading. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4086–4094.
- Cory Shain. 2023. Word frequency and predictability dissociate in naturalistic reading. *PsyArXiv preprint*.
- Cory Shain, Idan Asher Blank, Marten van Schijndel, William Schuler, and Evelina Fedorenko. 2020. fMRI reveals language-specific predictive coding during naturalistic sentence comprehension. *Neuropsychologia*, 138:107307.
- Cory Shain, Clara Meister, Tiago Pimentel, Ryan Cotterell, and Roger Levy. 2022. Large-scale evidence for logarithmic effects of word predictability on reading time. *PsyArXiv preprint*.
- Claude Elwood Shannon. 1948. A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423.
- Nathaniel J. Smith and Roger Levy. 2013. The effect of word predictability on reading time is logarithmic. *Cognition*, 128:302–319.
- Kushal Tirumala, Aram Markosyan, Luke Zettlemoyer, and Armen Agajanyan. 2022. Memorization without overfitting: Analyzing the training dynamics of large language models. In *Advances in Neural Information Processing Systems*, volume 35, pages 38274–38290.
- Ben Wang and Aran Komatsuzaki. 2021. GPT-J-6B: A 6 billion parameter autoregressive language model.
- Ethan G. Wilcox, Tiago Pimentel, Clara Meister, Ryan Cotterell, and Roger P. Levy. 2023. Testing the predictions of surprisal theory in 11 languages. *Transactions of the Association for Computational Linguistics*, 11:1451–1470.
- Mengzhou Xia, Mikel Artetxe, Chunting Zhou, Xi Victoria Lin, Ramakanth Pasunuru, Danqi Chen, Luke Zettlemoyer, and Veselin Stoyanov. 2023. Training trajectories of language models across scales. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics*, pages 13711–13738.
- Matthew D. Zeiler and Rob Fergus. 2014. Visualizing and understanding convolutional networks. In *Computer Vision – ECCV 2014*, pages 818–833.
- Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuhui Chen, Christopher DeWan, Mona Diab, Xian Li, Xi Victoria Lin, Todor Miaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. 2022. OPT: Open pre-trained Transformer language models. *arXiv preprint*, arXiv:2205.01068v4.

A Hyperparameters of LM Variants

The hyperparameters of model variants from the four LM families evaluated in this work are outlined in Table 1.

Model Variant	#L	#H	d_{model}	#Parameters
GPT-2 Small	12	12	768	~124M
GPT-2 Medium	24	16	1024	~355M
GPT-2 Large	36	20	1280	~774M
GPT-2 XL	48	25	1600	~1.6B
GPT-Neo 125M	12	12	768	~125M
GPT-Neo 1.3B	24	16	2048	~1.3B
GPT-Neo 2.7B	32	20	2560	~2.7B
GPT-J 6B	28	16	4096	~6B
GPT-NeoX 20B	44	64	6144	~20B
OPT 125M	12	12	768	~125M
OPT 350M	24	16	1024	~350M
OPT 1.3B	24	32	2048	~1.3B
OPT 2.7B	32	32	2560	~2.7B
OPT 6.7B	32	32	4096	~6.7B
OPT 13B	40	40	5120	~13B
OPT 30B	48	56	7168	~30B
OPT 66B	64	72	9216	~66B
Pythia 70M	6	8	512	~70M
Pythia 160M	12	12	768	~160M
Pythia 410M	24	16	1024	~410M
Pythia 1B	16	8	2048	~1B
Pythia 1.4B	24	16	2048	~1.4B
Pythia 2.8B	32	32	2560	~2.8B
Pythia 6.9B	32	32	4096	~6.9B
Pythia 12B	36	40	5120	~12B

Table 1: Hyperparameters of model variants whose surprisal estimates were examined in this work. #L, #H, and d_{model} respectively refer to number of layers, number of attention heads per layer, and embedding size.

B Surprisal Values as a Function of Training Steps

The proportion of surprisal values from the Pythia LM family as a function of training steps on each quintile of the four corpora can be found in Figures 7 (Natural Stories), 8 (Dundee), 9 (GECO), and 10 (Provo).

C SSEs From Regression Models as a Function of Training Steps

The SSEs from regression models containing surprisal predictors from the Pythia LM family as a function of training steps on each quintile of the four corpora can be found in Figures 11 (Natural Stories), 12 (Dundee), 13 (GECO), and 14 (Provo).

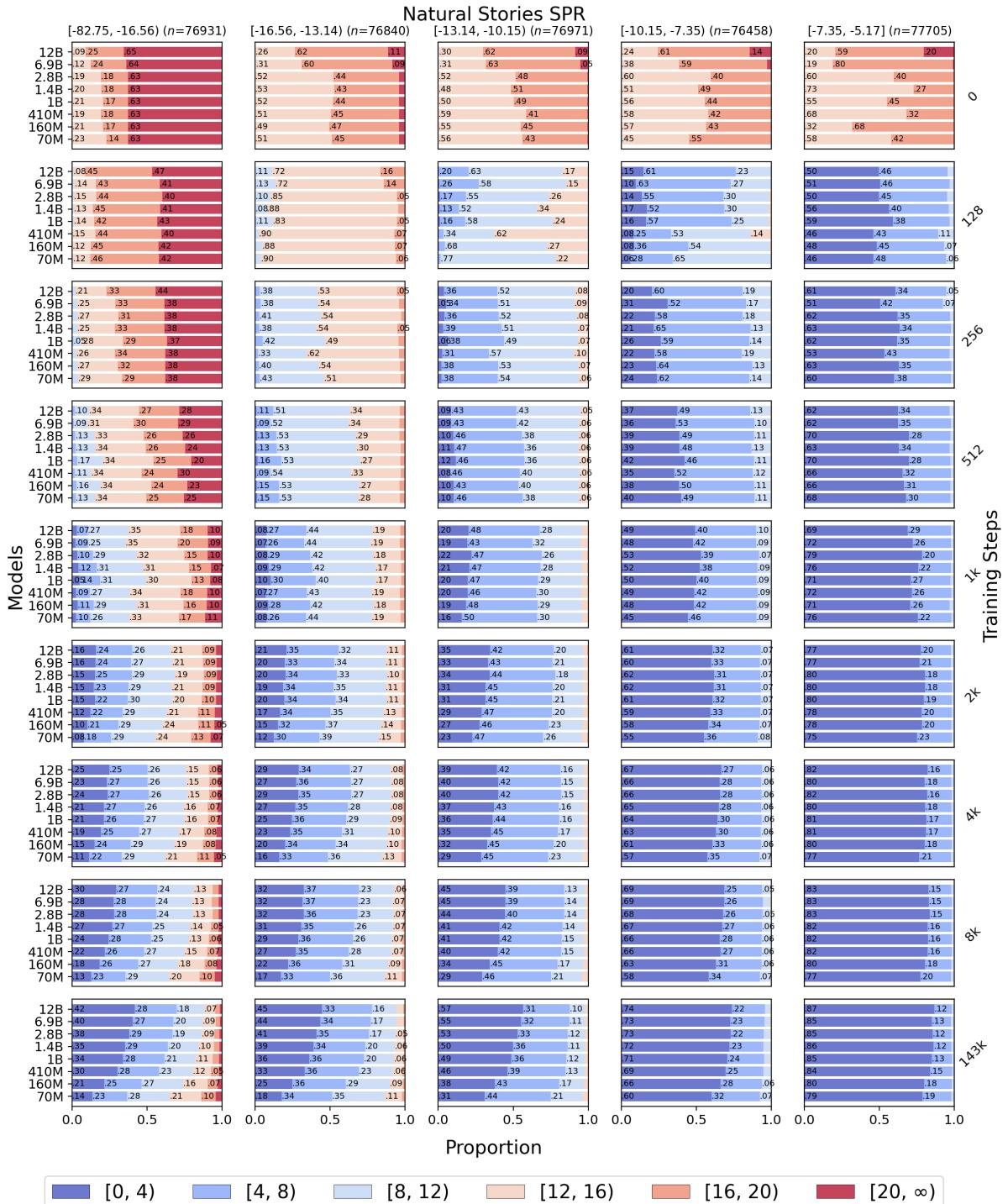


Figure 7: Proportion of surprisal values from Pythia model variants on each quintile of the Natural Stories Corpus as a function of training steps. Proportions that are greater than .05 are annotated.

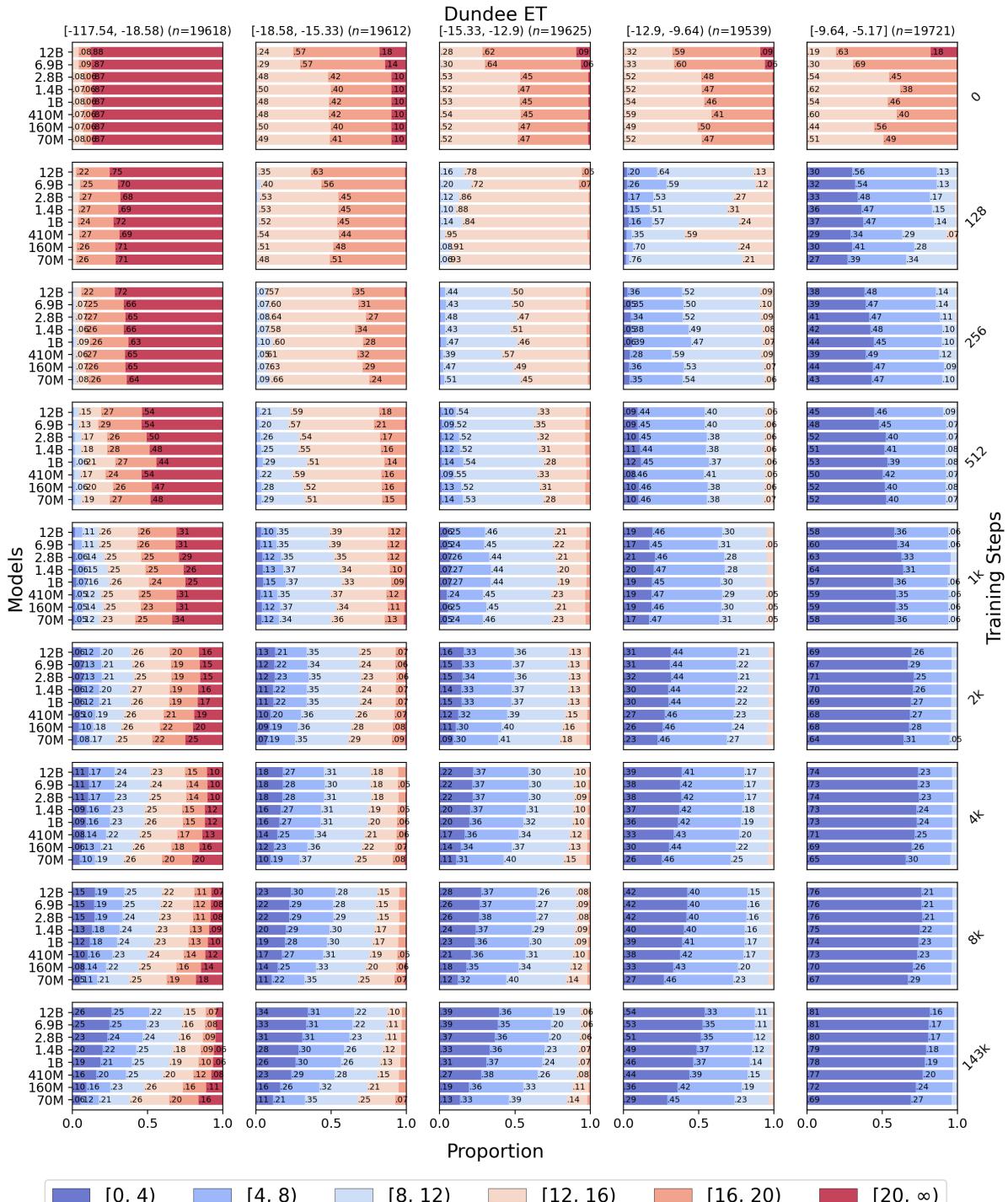


Figure 8: Proportion of surprisal values from Pythia model variants on each quintile of the Dundee Corpus as a function of training steps. Proportions that are greater than .05 are annotated.

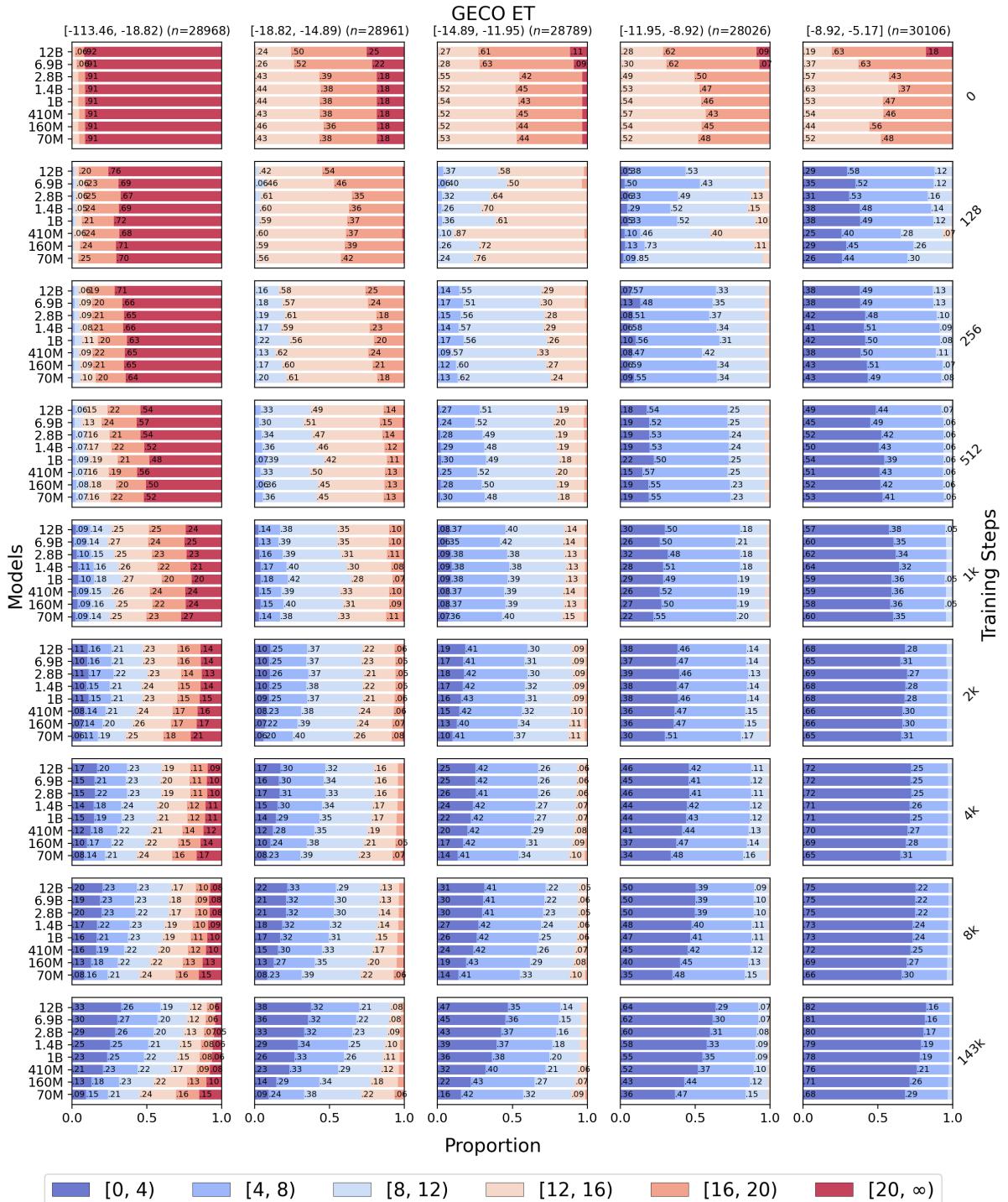


Figure 9: Proportion of surprisal values from Pythia model variants on each quintile of the GECO as a function of training steps. Proportions that are greater than .05 are annotated.

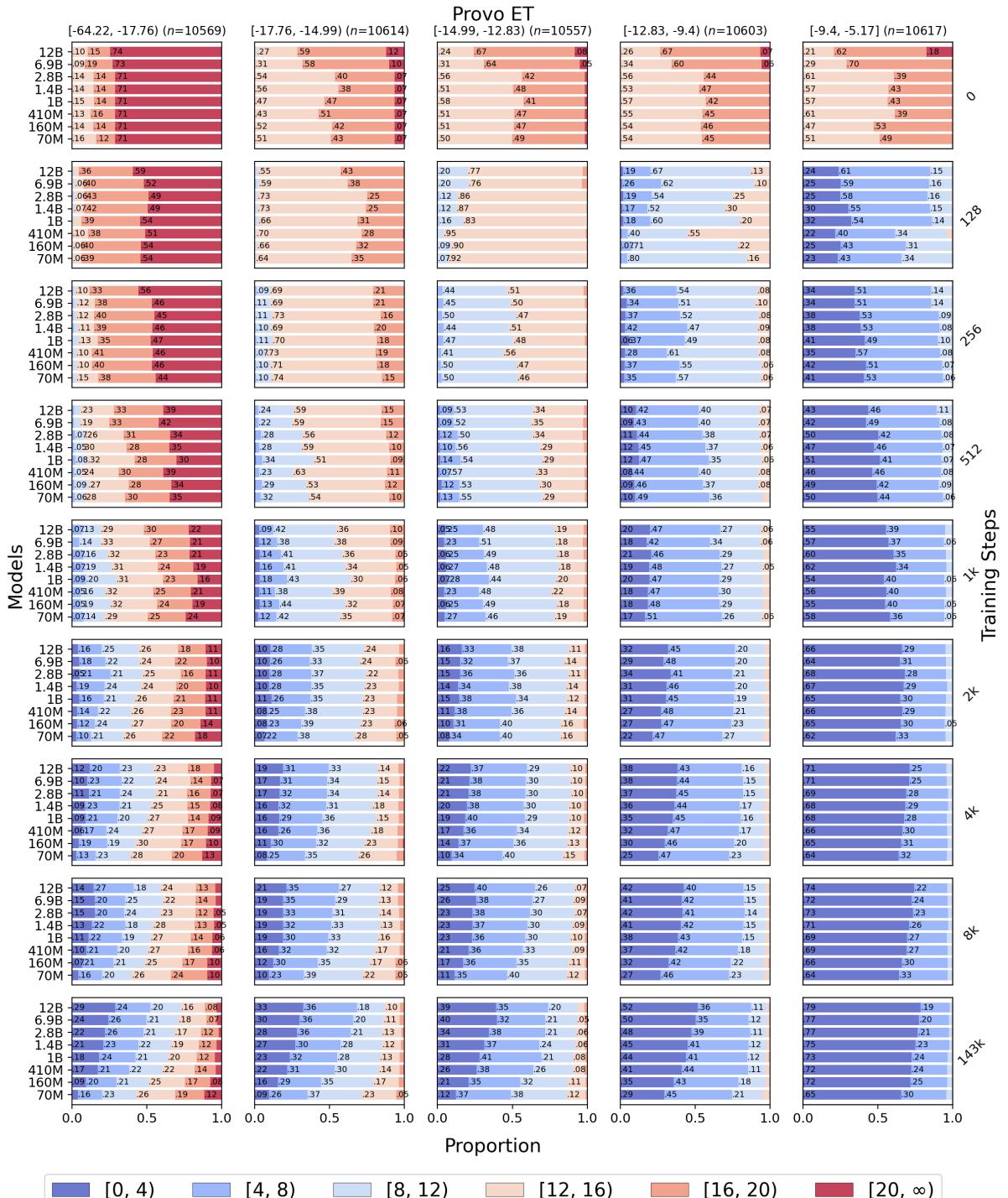


Figure 10: Proportion of surprisal values from Pythia model variants on each quintile of the Provo Corpus as a function of training steps. Proportions that are greater than .05 are annotated.

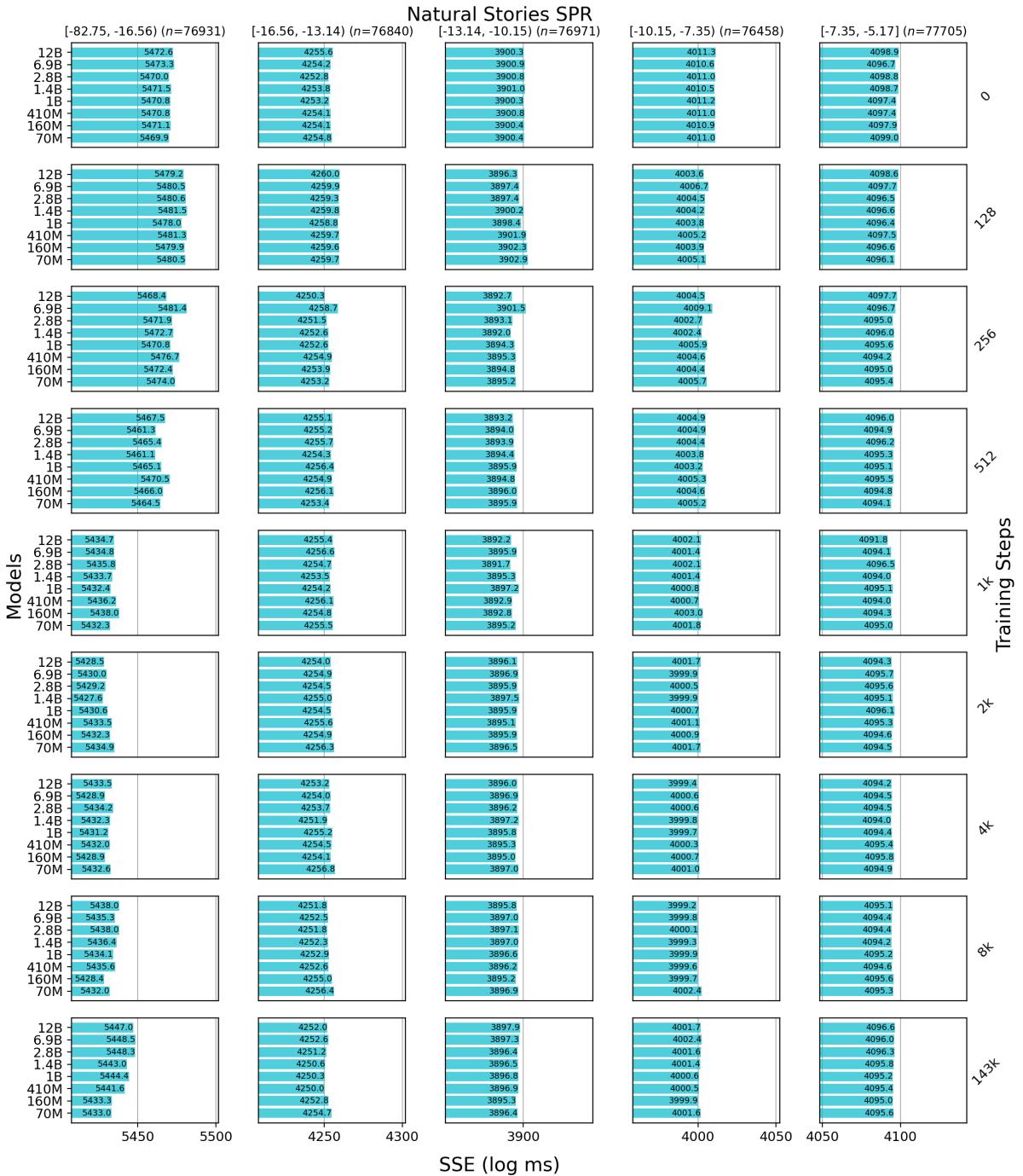


Figure 11: SSEs from regression models containing surprisal predictors from Pythia model variants on each quintile of the Natural Stories Corpus as a function of training steps. The columns of subplots share the scale but not the range of the x-axis for visual clarity.

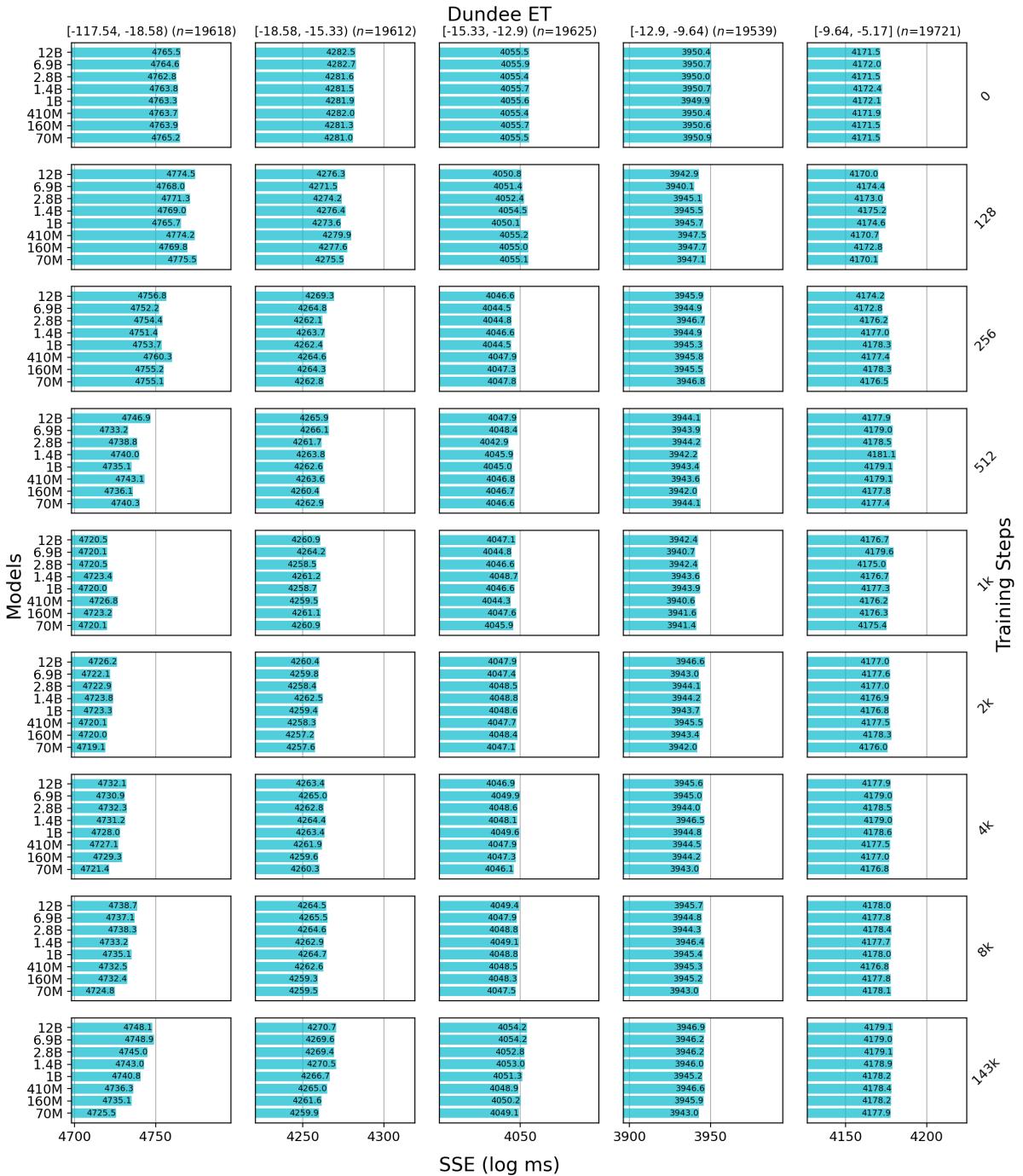


Figure 12: SSEs from regression models containing surprisal predictors from Pythia model variants on each quintile of the Dundee Corpus as a function of training steps. The columns of subplots share the scale but not the range of the x-axis for visual clarity.

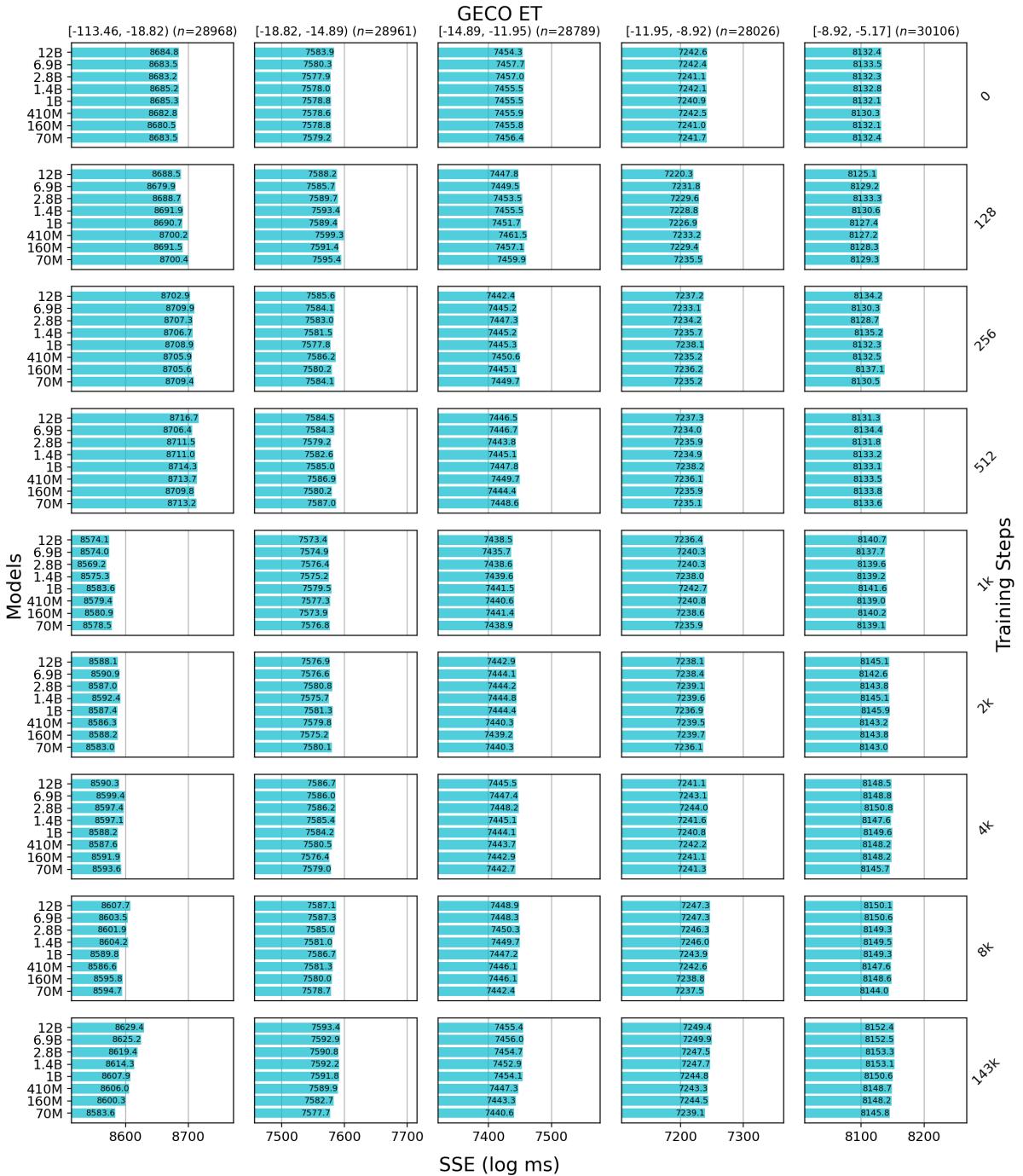


Figure 13: SSEs from regression models containing surprisal predictors from Pythia model variants on each quintile of the GECO as a function of training steps. The columns of subplots share the scale but not the range of the x-axis for visual clarity.



Figure 14: SSEs from regression models containing surprisal predictors from Pythia model variants on each quintile of the Provo Corpus as a function of training steps. The columns of subplots share the scale but not the range of the x-axis for visual clarity.