Uniform Complexity for Text Generation

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Abstract

Large language models (LLMs) have shown promising results in a wide array of generative NLP tasks, such as summarization and machine translation. In the context of narrative generation, however, existing models still do not capture factors that contribute to producing consistent text. For instance, it is logical that a piece of text or a story should be uniformly readable throughout and that this form of complexity should be controllable. As such, if the complexity of an input text prompt is rated first-grade reading level in the Flesch Reading Ease test, then the generated text continuing the plot should also be within this range of complexity. With this in mind, we introduce Uniform Complexity for Text Generation (UCTG), a new benchmark test which raises the challenge of making generative models observe uniform linguistic properties with respect to prompts. We experiment with over 150+ linguistically and cognitively motivated features for evaluating text complexity in humans and generative models. From our results, we find that models such as GPT-2 struggle to preserve the complexity of input prompts used in its generations, even if finetuned with professionally written texts\textsuperscript{1}.

1 Introduction

Consistency is key in all aspects of the storywriting process. A story has to have a consistent plot or story arc, observe a consistent use of factual information if needed, make use of consistent personas for characters, and follow a consistent writing style in order to be comprehensible (Guan and Huang, 2020; Zhang et al., 2022; Huang et al., 2023). While topic consistency is often used as a general metric for evaluating the quality of texts produced by narrative generation systems (Roemmele, 2021), an important aspect that has received less attention from the research community is the investigation of consistency of readability or complexity of texts.

When crafting a story, it is very reasonable for a writer to ensure that all sentences are readable by a specific target audience (i.e., first-grade learners). As such, one must take note of common words within the general vocabulary of readers belonging to a specific grade to avoid possible frustration in reading that will hinder effective comprehension (Gickling and Armstrong, 1978; Guevarra, 2011). Thus, a text’s complexity (and so the readability) depends largely on the writer’s capability to ensure that the complexity of words and sentences is consistent (Fountas and Pinnell, 1999; DuBay, 2004; 

\textsuperscript{1}https://github.com/imperialite/uniform-complexity-textgen/
Agrawal and Carpuat, 2019). In the text generation process, since the output of generative models is controlled by the prompt, it is essential that the complexity of the output to be consistent with the input prompt. Figure 1 shows an ideal scenario where a prompt given by a human has the same level of reading difficulty (66.9) as the generated text by a GPT-2 model (61.9) based on the Flesch Ease formula (Flesch, 1948). The interpretation of Flesch Ease scores obtained means both texts can be read easily by Grade 8 and 9 learners.

Generally, the complexity of a narrative or any piece of text at hand can be measured by a multitude of content-based and linguistic factors. Some measures that have been explored through the years include syntactic complexity as equivalence of high-proficiency writing through the presence of qualified syntactic phrases or chunks such as words from a noun or verb phrase (Beers and Nagy, 2009; McNamara et al., 2010; Roemmele et al., 2017), discourse complexity by aggregating the presence of entities of a text such as mentions people, organizations, and locations which can lead to increased working memory burden (Feng et al., 2009), and vocabulary complexity by matching words from the text associated with a specific age-based difficulty level from developmental studies (Kuperman et al., 2012; Vajjala and Meurers, 2016) to name a few. These factors, when extracted from texts for evaluating complexity, usually follow a general linear property where the complexity of a text also increases as the value of a measured feature is increased (Genzel and Charniak, 2002).

In this study, we aim to answer the following research question: can large language models (LLMs) generate responses that observe uniform complexity with the prompt? To answer this, we introduce the novel task of Uniform Complexity for Text Generation (UCTG) with the aim of investigating responses obtained from any arbitrary generative language models used in story generation With GPT-2 models as test case, we explore how the outputs generated by LLMs relate to prompts and continuations given by humans, in relation to these linguistic features. Specifically, we make the following major contributions:

1. We empirically show the inconsistencies in linguistic characteristics exhibited by LLMs, specifically GPT-2, with respect to the complexity of the prompts used. We cover a wide array of linguistic complexity features (total 160) used for evaluating text complexity in this process. We also report that fine-tuned models, even trained on uniformly complex and professionally written text, do not alleviate this problem.

2. Despite inconsistencies with respect to the prompts, we show that there are some similarities with the way GPT-2 models (fine-tuned or not) and humans generate continuations, such as the preference of words from pre-defined word familiarity vocabularies such as Age-of-Acquisition and SubtlexUS.

3. Scoping our narrative more broadly, we sketch possible careful considerations when framing UCTG as an automatic evaluation metric for NLG systems due to the scalability of text complexity across language-related tasks.

2 Benchmark Task Description
The proposed evaluation task can be generally adapted to any NLG framework as long as texts are both the input and output. In the case of a narrative generation setting, given a series of prompts where each one is made up of a few sentences $P = \{p_1, p_2, \ldots, p_n\}$ and their continuations $C = \{c_1, c_2, \ldots, c_n\}$ by a model $M$, a linguistic feature function $F$ processes instances from both the prompt and continuation sets to get their corresponding measures $F(p_n) \in \mathbb{R}$ and $F(c_n) \in \mathbb{R}$. All calculations performed by $F$ are normalized$^2$ with either the number of word counts or a similar variable to avoid higher values from longer generated texts. A statistical test is then applied using the two groups to measure the significant differences in each linguistic complexity feature variable.

3 Generation Setup
We describe the training recipes and resources used for exploring UCTG in human and GPT-2 models.

3.1 Human Prompt and Continuation Data
For the compilation of prompts and human continuation as a benchmark, we used the WritingPrompts$^3$ dataset collected by Fan et al. (2018). This dataset is derived from the r/WritingPrompts community of the Reddit platform where it allows

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$^2$This is a common practice in text complexity research to mitigate the effects of length in feature values (Lu, 2012).

$^3$www.reddit.com/r/WritingPrompts/
users to post story premises in various contexts and genres for other members to continue with their own ideas and creativity. The current compilation is divided into train, test, and validation splits. Given the nature of this task, we only used the test split which contains 15,138 pairs. In addition to the data preprocessing steps done by DeLucia et al. (2021), we handpicked prompts with at least 30 words in length to ensure that the neural models will have enough context for the generation phase while limiting human continuation texts to a minimum of 150 words and a maximum of 300 words to avoid long-range memory limitation in the small GPT-2 model used (Sun et al., 2021). Overall, we arrived at a total of 941 prompt-human continuation pairs as the benchmark for the task.

3.2 Generation Models

To test whether large neural language models are capable of UCTG, we selected the GPT-2 class of models (Radford et al., 2019) for analysis due to its notable extensive use in the NLP community for the narrative generation task (See et al., 2019; Xu et al., 2020; Akoury et al., 2020; Chang et al., 2021). Aside from human generations at hand, we used three variations of GPT-2 for comparison as listed below:

Base GPT-2. This model is the standard off-the-shelf medium version with 355M parameters from Huggingface. We refer to this model as the base version as it is used without any fine-tuning.

Finetuned GPT-2 for General Narrative Generation (DeLucia et al., 2021). This model uses the GPT-2 medium version that has been fine-tuned for general narrative generation using the same WRITINGPROMPTS dataset in Fan et al. (2018) and has been optimized with the best hyperparameters for maximum fluency and diversity of content.

Finetuned GPT-2 with Uniformly Complex Texts. This model also uses the GPT-2 medium version but we fine-tuned it using datasets from NEWSLELA and ELG. NEWSLELA is a collection of 10,787 professionally-written news articles in English with over 4-5 different variations in reading levels (Scarton et al., 2018; Xu et al., 2016, 2015). We also add another data source from the European Language Grid (ELG) compiled by Breuker (2022) which contains 1,200 curated stories in all levels of the Common European Framework of Reference for Languages (CEFR). We refer to both of these language resources as professionally-written and uniformly complex as they have been produced and classified by expert writers in contrast to the WRITINGPROMPTS dataset in Fan et al. (2018) where the authors of narrative continuations are Reddit users and are non-experts. For the fine-tuning setup, we use the same recipe found in DeLucia et al. (2021). We upload the finetuned model in Huggingface for public access.

For the decoding setup, DeLucia et al. (2021) reports that the best values for nucleus sampling or top-p for the narrative generation task range from 0.70 to 0.90 wherein generated stories are more vivid and of better quality as evaluated through human and automatic means. Thus, for this work, we set top-p to 0.90 for all GPT-2 models.

4 Testing for (In)consistencies from the Prompt-Continuation Pairs

For the first experiment, we test for possible significant differences in the complexity values of the prompts and generations of the three variations of GPT-2 models described previously plus generations from humans. We use the Welch t-test (Welch, 1947) with Bonferroni correction resulting in a new alpha level of $\alpha = 0.0125$ (0.05/4). We extracted 160 linguistic features using the LingFeat tool by Lee et al. (2021) for the variables of interest. The tool covers the extraction of surface, lexical, phrasal, tree structure, type token, psycholinguistics, and formula-based readability features as further detailed in the subsections below. We only used the normalized or average-based linguistic complexity features (ex. count of noun POS / total count of words) instead of total raw counts to avoid bias or reaching extremely high values for longer sentences. As a reference for labels of models used in the succeeding tables, we use GPT2 for the base model with no fine-tuning, GPT2-DF for the model fine-tuned for general narrative generation, and GPT2-UF for the model fine-tuned with uniformly complex dataset.

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Footnotes:

1. https://huggingface.co/gpt2
2. https://newsela.com/data/
3. https://live.european-language-grid.eu/catalogue/corpus/9477
4. https://huggingface.co/josephimperial/uniform-complex-gpt2-med
For ease of readability and display purposes, we report the \( p \)-values from the result of the Welch test for the tables per linguistic group in the succeeding sections. We also include an extensive set of barplot visualizations in Appendix A arranged alphabetically for ease of referencing.

### 4.1 Shallow Features

For our first feature set, we looked at 8 shallow or surface-based textual features as shown in Table 1 such as product and square root of total tokens by total sentences, log densities of tokens to sentences, average token count per sentence, average syllable count per sentence and per token, and average character count per sentence and token. These linguistic features have been extensively used text complexity assessment in a wide range of languages such as in English (Flesch, 1948), French (François and Miltsakaki, 2012) and Filipino (Imperial and Ong, 2021). From the result, all of the mentioned features for the four groups appear to be significantly different with respect to the complexity of the prompt except for average characters per token for the finetuned GPT-2 model with uniformly complex data. From this, we posit that both humans and GPT-2 models, regardless of applied fine-tuning, generally ignore shallow or surface-based characteristics of texts with respect to the prompt.

| Feature                        | Human | GPT2 | GPT2-DF | GPT2-UF |
|-------------------------------|-------|------|---------|---------|
| Total token x Total sent      | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Sept Total token x Total sent | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Log token / Log sent          | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Avg token sent                | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Avg Syll sent                 | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Avg Syll token                | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Avg Chars sent                | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Avg Chars token               | 0.0020| 0.0000| 0.0000  | 0.1281  |

Table 1: Shallow based features.

### 4.2 Traditional Formula-Based Features

Formula-based features for readability assessment also stem from a combination of surface-based features such as word length, sentence length, and occurrence from a pre-defined dictionary of words. We covered 6 metrics such as Flesch-Kincaid (Kincaid et al., 1975), New Automated Readability Index (NARI) (Smith and Senter, 1967), Coleman-Liau (Coleman and Liau, 1975), SMOG (McLaughlin, 1969), Gunning-Fog (Gunning et al., 1952), and Linsear (Kclare, 1974). Due to their ease of use, formulas such as the Flesch-Kincaid Reading Ease are integrated into most text-based applications. From the results in Table 2, the majority of the narrative continuations from humans, base GPT-2 model, and both the finetuned GPT-2 models were significantly different except for two. The formula for NARI is the only one that uses the number of characters as a predictor, which may signal that human-continued texts are more sensitive to character count. In addition, the base GPT-2 model obtaining non-significance for text dissimilarity on Flesch-Kincaid may indicate potential preservation of complexity. However, this is a one-off and is not consistent for all formulas explored.

| Feature         | Human | GPT2 | GPT2-DF | GPT2-UF |
|-----------------|-------|------|---------|---------|
| Flesch-Kincaid  | 0.0008| 0.0831| 0.0000  | 0.0000  |
| NARI            | 0.3535| 0.0111| 0.0000  | 0.0000  |
| Coleman-Liau    | 0.0000| 0.0000| 0.0000  | 0.0000  |
| SMOG            | 0.0000| 0.0000| 0.0026  | 0.0000  |
| Gunning-Fog     | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Linsear         | 0.0000| 0.0005| 0.0000  | 0.0000  |

Table 2: Traditional formula-based features.

### 4.3 Part of Speech Features

We further the analysis by looking deeper into the text structure via part-of-speech (POS) tags. For this study, syntactic concepts covering nouns, verbs, adverbs, adjectives, subordinating clauses and conjunction, coordinating clauses and conjunction and prepositional phrases were used as predictors to calculate the densities of prompts and text continuations in both sentence and token level aspect (Heilman et al., 2007; Lu, 2012). Table 3 details 47 ratio and average-based predictors, quantifying POS complexities of human and neural model text continuations. Overall, the finetuned GPT-2 model for general story generation obtained the least number of complexity features that are significantly different from the prompt with 31 (16 features non-significant). This is followed by the human-generated continuations with 33 (14 features non-significant), the baseline GPT-2 with 37 (10 features non-significant), and GPT-2 model trained from uniformly complex data coming in last with 41 (6 features non-significant). One clear observation that can be derived from the POS features is that all non-significance from the finetuned GPT-2 model for uniformly complex data overlaps with the continuations from humans and the finetuned GPT-2 model for general story generation, especially for features related to the average use of adjective words, content words, and coordi-
nating conjunctions. We infer that the additional fine-tuning process done for neural models encourages some level of uniformity of usage of the said grammatical entities with respect to prompts. Interestingly, fine-tuning on a general story completion dataset encourages more sensitivity to these features compared to using uniformly complex text. This is surprising as one might expect increased consistency in the generated output when trained on such data. This result further highlights the need for the evaluation of complexity in language model outputs and for this task, which is non-trivial to solve.

Table 3: Part of speech based features.

| Feature | Human | GPT2 | GPT2-DF | GPT2-UF |
|---------|-------|------|---------|---------|
| Avr Noun POS sent | 0.0000 | 0.0194 | 0.0000 | 0.0000 |
| Avr Noun POS token | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Noun POS to Adj POS | 0.0002 | 0.1467 | 0.0025 | 0.0000 |
| Noun POS to Verb POS | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Noun POS to Advrb POS | 0.0000 | 0.0000 | 0.3215 | 0.0000 |
| Noun POS to SubrdConj | 0.0000 | 0.0000 | 0.0096 | 0.0000 |
| Noun POS to CordConj | 0.0000 | 0.0814 | 0.0002 | 0.0118 |
| Avr Verb POS sent | 0.1531 | 0.0000 | 0.0000 | 0.0000 |
| Avr Verb POS token | 0.0000 | 0.0629 | 0.0000 | 0.0000 |
| Verb POS to Adj POS | 0.0244 | 0.0006 | 0.0000 | 0.0006 |
| Verb POS to Noun POS | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Verb POS to Advrb POS | 0.2502 | 0.0000 | 0.0000 | 0.0123 |
| Verb POS to SubrdConj | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Verb POS to CordConj | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Avr Adj POS sent | 0.0557 | 0.0735 | 0.0000 | 0.0000 |
| Avr Adj POS token | 0.7909 | 0.0013 | 0.6105 | 0.0249 |
| Adj POS to Noun POS | 0.1982 | 0.0227 | 0.0000 | 0.0000 |
| Adj POS to Verb POS | 0.0000 | 0.0092 | 0.0244 | 0.0000 |
| Adj POS to Advrb POS | 0.0000 | 0.0000 | 0.0506 | 0.0000 |
| Adj POS to SubrdConj | 0.0000 | 0.0000 | 0.0408 | 0.0000 |
| Adj POS to CordConj | 0.0000 | 0.0011 | 0.5120 | 0.0000 |
| Avr Advrb POS sent | 0.0000 | 0.0411 | 0.0000 | 0.0003 |
| Avr Advrb POS token | 0.0000 | 0.0608 | 0.3566 | 0.0000 |
| Advrb POS to Adj POS | 0.0000 | 0.0726 | 0.0249 | 0.0000 |
| Advrb POS to Noun POS | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Advrb POS to Verb POS | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Advrb POS to SubrdConj | 0.0000 | 0.0000 | 0.0138 | 0.0000 |
| Advrb POS to CordConj | 0.0000 | 0.0027 | 0.5228 | 0.0000 |
| Advrb POS to CordCobj | 0.0000 | 0.0247 | 0.5228 | 0.0000 |
| Advrb SubrdConj sent | 0.2546 | 0.0000 | 0.0000 | 0.0000 |
| Advrb SubrdConj token | 0.4888 | 0.0000 | 0.0023 | 0.0000 |
| SubrdConj POS to Adj POS | 0.1985 | 0.0000 | 0.2602 | 0.0000 |
| SubrdConj POS to Noun POS | 0.2955 | 0.0000 | 0.0000 | 0.0000 |
| SubrdConj POS to Verb POS | 0.0002 | 0.0000 | 0.0000 | 0.0000 |
| SubrdConj POS to Advrb POS | 0.0002 | 0.0000 | 0.0000 | 0.0000 |
| SubrdConj POS to CordConj | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Avr CordConj POS sent | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Avr CordConj POS token | 0.2407 | 0.0000 | 0.4773 | 0.0000 |
| CordConj POS to Adj POS | 0.2080 | 0.0000 | 0.1113 | 0.0000 |
| CordConj POS to Noun POS | 0.2194 | 0.0000 | 0.0000 | 0.0000 |
| CordConj POS to Verb POS | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| CordConj POS to Advrb POS | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| CordConj POS to SubrdConj | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Avr Content Words sent | 0.0017 | 0.6532 | 0.0000 | 0.0000 |
| Avr Content Words token | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Avr Function Words token | 0.0019 | 0.0000 | 0.0000 | 0.0000 |
| Content to Function Words | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Table 4: Type token based features.

| Feature | Human | GPT2-DF | GPT2-UF |
|---------|-------|---------|---------|
| Simple TTR | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Correlated TTR | 0.0000 | 0.0109 | 0.0000 | 0.0553 |
| BiLogarithmic TTR | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Uber Index | 0.6039 | 0.0000 | 0.0000 | 0.0000 |
| Lexical Diversity | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Table 5: Lexical variation based features.

4.5 Lexical Variation Features

In complement to calculating ratios and averages of word-level POS complexities, lexical variation can also signal difficulty via densities of unique grammatical components (Lu, 2012). Table 5 describes 12 lexical variation-based features focusing on simple, squared, and corrected versions of unique counts of POS such as nouns, verbs, ad-
jectives and adverbs normalized its total in a sentence. From the results, only the unique adverb and verb variations from the human-generated, baseline GPT-2 model, and uniformly complex GPT-2 model obtained non-significance. Complementing the results previously seen in POS features, we further see the evidence of how fine-tuning may impact text continuations, especially on the usage of verbs that usually denote events and actions in a story.

4.6 Phrasal Features

Moving on to longer sequences of part-of-speech complexities, we also measure phrase-level linguistic features. Table 7 shows 42 phrase-based features centering on token and sentence ratios of grammatical components such as noun phrases, verb phrases, adverbial phrases, adjectival phrases, subordinate phrases and prepositional phrases. Overall, the human continuation obtained 12 phrasal-based features, which were uniform with respect to the prompt, 13 for the base GPT-2, and 7 for the finetuned GPT-2 model for general story generation, and 8 for the finetuned GPT-2 model with uniformly complex data. From this result, we posit that not performing fine-tuning of the GPT-2 model preserves the syntactic structure of the sentence at phrase level but not at finegrained word level as seen in POS features in Table 3. We also see a connection as to why Transformer-based models are often finetuned for paraphrasing tasks to trigger the required number of lexical swaps and syntactic diversity (Witteveen and Andrews, 2019; Krishna et al., 2020).

| Feature                     | Human | GPT2 | GPT2-DF | GPT2-UF |
|-----------------------------|-------|------|---------|---------|
| Avr Noun phrs sent          | 0.0280| 0.0000| 0.0000  | 0.0000  |
| Avr Noun phrs token         | 0.0000| 0.0121| 0.0000  | 0.0000  |
| Noun phrs to Verb phrs      | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Noun phrs to SubClause      | 0.0000| 0.0757| 0.0222  | 0.8315  |
| Noun phrs to Prep phrs      | 0.0047| 0.0067| 0.0000  | 0.0064  |
| Noun phrs to Adj phrs       | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Noun phrs to Adv phrs       | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Avr Verb phrs sent          | 0.2605| 0.0000| 0.0008  | 0.0000  |
| Avr Verb phrs token         | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Verb phrs to Noun phrs      | 0.0335| 0.0000| 0.0000  | 0.0000  |
| Verb phrs to SubClause      | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Verb phrs to Prep phrs      | 0.5188| 0.0168| 0.0000  | 0.0000  |
| Verb phrs to Adj phrs       | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Verb phrs to Adv phrs       | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Avr SubClause sent          | 0.7199| 0.0000| 0.0021  | 0.2506  |
| Avr SubClause token         | 0.0003| 0.0000| 0.0000  | 0.0000  |
| SubClause to Noun phrs      | 0.2813| 0.0000| 0.0000  | 0.0000  |
| SubClause to Verb phrs      | 0.0033| 0.8824| 0.0000  | 0.2659  |
| SubClause to Prep phrs      | 0.0160| 0.2844| 0.0000  | 0.0997  |
| SubClause to Adj phrs       | 0.0000| 0.0000| 0.0000  | 0.0000  |
| SubClause to Adv phrs       | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Avr Prep phrs sent          | 0.1307| 0.0000| 0.0000  | 0.0000  |
| Avr Prep phrs token         | 0.2976| 0.6734| 0.0000  | 0.0000  |
| Prep phrs to Noun phrs      | 0.1831| 0.5031| 0.0000  | 0.0000  |
| Prep phrs to Verb phrs      | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Prep phrs to SubClause      | 0.0000| 0.0288| 0.0014  | 0.0197  |
| Prep phrs to Adj phrs       | 0.0000| 0.0000| 0.1481  | 0.0000  |
| Prep phrs to Adv phrs       | 0.0000| 0.0000| 0.1013  | 0.0727  |
| Avr Adj phrs sent           | 0.0000| 0.0029| 0.2439  | 0.7460  |
| Avr Adj phrs token          | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Adj phrs to Noun phrs       | 0.0002| 0.0075| 0.0000  | 0.0006  |
| Adj phrs to Verb phrs       | 0.3468| 0.2768| 0.4599  | 0.5966  |
| Adj phrs to SubClause       | 0.0000| 0.0014| 0.0000  | 0.0026  |
| Adj phrs to Prep phrs       | 0.6291| 0.7919| 0.0000  | 0.0173  |
| Adj phrs to Adv phrs        | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Avr Adv phrs sent           | 0.0000| 0.0003| 0.0000  | 0.0000  |
| Avr Adv phrs token          | 0.0000| 0.3127| 0.0000  | 0.0000  |
| Adv phrs to Noun phrs       | 0.0000| 0.9194| 0.4361  | 0.0000  |
| Adv phrs to Verb phrs       | 0.0000| 0.0000| 0.0000  | 0.0004  |
| Adv phrs to SubClause       | 0.0000| 0.7101| 0.2759  | 0.0000  |
| Adv phrs to Prep phrs       | 0.0000| 0.0603| 0.0000  | 0.0000  |
| Adv phrs to Adj phrs        | 0.0000| 0.0000| 0.0000  | 0.0000  |

Table 7: Phrasal based features.

4.7 Syntax Tree Features

Following the results of phrase-based features in Table 7, analyzing the difference in parse tree depth is a unique and interesting way of measuring readability as done in Schwarm and Ostendorf (2005). Table 6 describes 4 syntax tree height-based features including average heights of regular and flattened trees per token and sentence. From the result, only the human-generated texts as it obtained uniformity with the prompts as evidenced by features such as average regular tree height and average feature tree height at the sentence level, while none for the GPT-2 models. This suggests that neural model-based generated texts do not conform to the one property of syntax, such as parse tree height, when generating texts, despite the models themselves having access to a significant amount of syntactic information.

| Feature                     | Human | GPT2 | GPT2-DF | GPT2-UF |
|-----------------------------|-------|------|---------|---------|
| Avr Tree height sent        | 0.0326| 0.0000| 0.0002  | 0.0000  |
| Avr Tree height token       | 0.0000| 0.0000| 0.0000  | 0.0000  |
| Avr Ftree height sent       | 0.1125| 0.0000| 0.0000  | 0.0000  |
| Avr Ftree height token      | 0.0000| 0.0000| 0.0000  | 0.0000  |

Table 6: Syntax tree based features.

4.8 Psycholinguistic and Word Familiarity Features

We also look at psycholinguistic and word familiarity variables in reading using external wordlists such as the Age-of-Acquisition (AOA) database compiled by Kuperman et al. (2012) which contains over 30,000 English content words and the SubtlexUS by (Brysbaert and New, 2009) which is a compilation of over 74,000-word forms with frequency values extracted from 8,000 general films and series. These special databases contain words that are associated with various age levels that children are expected to learn when they reach the
stage. The works of Vajjala and Meurers (2016) and Chen and Meurers (2016) both have leveraged on these predictors in readability assessment and text familiarity. Using the LingFeat tool, we extract over 26 token, lemma, and sentence-based normalizations of AOA and SubtlexUS variations. Results from Table 8 show that not a single model has coincided with each other in terms of uniform features. The base GPT-2 model’s continuations are all significantly different from the prompts with respect to the psycholinguistic features used. The finetuned GPT-2 model only obtained non-significance from the averages of token-based features from the SubtlexUS dataset, and no uniformity is seen for the GPT-2 model finetuned with uniformly complex text. This suggests that fine-tuning for general story generation may introduce some control on the use of English content words but cannot be generalized to all types of fine-tuning.

For the last linguistic feature set investigated, we look at discourse in the form of averages of unique and non-unique entity presence that can affect working memory load and the local coherence distance measures which captures distribution and transitions of entities in a passage (Barzilay and Lapata, 2008; Guinaudeau and Strube, 2013). Feng et al. (2009) previously applied these cognitively motivated features for assessing reading difficulty in the case of adults with intellectual disabilities. Table 9 shows the 10 discourse-level features extracted from the prompt-continuation pairs where the majority of the features have non-uniformity for both humans and GPT-2 models. Without any observable pattern of uniformity, this finding generally suggests that the generated continuations have dissimilar levels of dependencies with respect to the prompts and vice versa.

### Table 9: Discourse based features.

| Feature           | Human | GPT2 | GPT2-DF | GPT2-UF |
|-------------------|-------|------|---------|---------|
| Avr Entity sent   | 0.0000| 0.0000| 0.0000 | 0.0000 |
| Avr Entity token  | 0.0000| 0.0000| 0.0000 | 0.0000 |
| Avr Uniq Entity sent | 0.0000| 0.0000| 0.0000 | 0.0000 |
| Avr Uniq Entity token | 0.0000| 0.0000| 0.0000 | 0.0000 |
| Local Coherence PW | 0.0000| 0.0000| 0.0087 | 0.0000 |
| Local Coherence PU | 0.0000| 0.0000| 0.0000 | 0.0000 |
| Local Coh Dist PA  | 0.0000| 0.0000| 0.0107 | 0.0000 |
| Local Coh Dist PW  | 0.0000| 0.0000| 0.0107 | 0.0000 |
| Local Coh Dist PU  | 0.0000| 0.0000| 0.0000 | 0.0000 |

5 Similarities Between Human and Model Generations

Aside from prompt-wise comparison, we also look at which linguistic complexity features from the GPT-2 models have some form of correlation with human continuations. This experiment aims to investigate which neural story generation models are potentially closer in producing more human-like text with respect to linguistic characteristics. For this, we use Pearson correlation to do the continuation-wise analysis and extract the top correlated features described in Table 10. From the results, all GPT-2 models obtained a minimum of six features from the psycholinguistics category referencing Age-of-Acquisition and SubtlexUS databases as top correlated features with human-generated texts. With this, we infer that even if there may be inconsistencies with respect to the prompts, the continuations from neural models for story generation have some level of similarity with human continuation against complexity features such as content word usage and word familiarity from the SubtlexUS database. This evidence is further strengthened by triple-occurring features across all GPT-2 models in the Table, which specifically include incidence of Age-of-Acquisition lemmas and words and tokens matched from the SubtlexUS databases.

| Feature           | Human | GPT2 | GPT2-DF | GPT2-UF |
|-------------------|-------|------|---------|---------|
| Avr Entity sent   | 0.0000| 0.0000| 0.0087 | 0.0000 |
| Avr Entity token  | 0.0000| 0.0000| 0.0000 | 0.0000 |
| Avr Uniq Entity sent | 0.0000| 0.0000| 0.0000 | 0.0000 |
| Avr Uniq Entity token | 0.0000| 0.0000| 0.0000 | 0.0000 |
| Local Coherence PW | 0.0000| 0.0000| 0.0087 | 0.0000 |
| Local Coherence PU | 0.0000| 0.0000| 0.0000 | 0.0000 |
| Local Coh Dist PA  | 0.0000| 0.0000| 0.0107 | 0.0000 |
| Local Coh Dist PW  | 0.0000| 0.0000| 0.0107 | 0.0000 |
| Local Coh Dist PU  | 0.0000| 0.0000| 0.0000 | 0.0000 |

Table 8: Psycholinguistics and word familiarity based features.

### 4.9 Discourse Features

For the last linguistic feature set investigated, we look at discourse in the form of averages of unique and non-unique entity presence that can affect working memory load as well as local coherence distance measures which captures distribution and transitions of entities in a passage (Barzilay and Lapata, 2008; Guinaudeau and Strube, 2013). Feng et al. (2009) previously applied these cognitively motivated features for assessing reading difficulty in the case of adults with intellectual disabilities. Table 9 shows the 10 discourse-level features extracted from the prompt-continuation pairs where the majority of the features have non-uniformity for both humans and GPT-2 models. Without any observable pattern of uniformity, this finding generally suggests that the generated continuations have dissimilar levels of dependencies with respect to the prompts and vice versa.
6 Benchmarking NLG Systems with UCTG

The evaluation of natural language generation (NLG) systems is an important process toward ensuring their usability, accessibility, and accuracy in practice. This research area has become one of the most active in the NLP community in recent years due to the rise of more complex and powerful generative models (Gehrmann et al., 2021; Caglayan et al., 2020). Synthesizing the results shown from Sections 4 and 5 in this study reporting the current inconsistencies of finetuned GPT-2 models in generating uniformly complex texts, one may reason out the potential of UCTG as a benchmark task for existing NLG systems to gather attention and encourage work from the research community. For this proposition, we highlight three major points below as insights that may be considered for building more uniformly complex text generation models.

6.1 Advantages of considering user background.

Despite being the main focus in readability assessment research, text complexity is a century-old research area that dates back to the 1920s (Thorndike, 1927), and is a task-agnostic multi-faceted variable that can be applied in almost all language-related experiments. This makes UCTG, unlike other automatic metrics restricted to certain tasks such as BLEU (Papineni et al., 2002) or METEOR (Banerjee and Lavie, 2005) for machine translation, likely to have more impact towards accessibility and user-dependence of NLG systems if carefully considered. However, the current methods for evaluating text complexity are wide-ranging—as evidenced by the 160 linguistic features used in this study which can potentially be used as predictors for building complexity assessment models. Thus, we recommend a user-centric approach for UCTG where the linguistic predictors that will be used for evaluation are catered towards specific groups of users and their language capabilities. We see strong promising support for this direction, as evidenced in previous works where different word complexity predictors (e.g. syllable length) are correlated between subgroups of people with distinct language backgrounds such as native vs. non-native English speakers (Gooding and Tragut, 2022; Gooding et al., 2021).

6.2 Advantages of using language-specific readability metrics.

Current disadvantages of automatic evaluation metrics include weak correlation and reflection with human preferences as well as limitations in considering finer-grained information during assessment (ex. sentence-level processing) (Sai et al., 2021; Reiter, 2018; Reiter and Belz, 2009; Stent et al., 2005). Moreover, works on expanding NLG research towards multilingual data have also gained significant traction (Gehrmann et al., 2021; Hu et al., 2020; Ponti et al., 2020). In this regard, more and more efforts from the NLG community, such as the work of Novikova et al. (2017), for instance, support the proposal for data-independent automatic evaluation methods, especially for multilingual and cross-domain applications. While this proposition has clear benefits, there is still limited work on text complexity research on the transferability of linguistic complexity predictors from one language to another. And so far, previous works have emphasized the importance of still using language-specific complexity predictors such as in Imperial and Kochmar (2023) and Imperial et al. (2022) for...
Philippine languages, and Weiss et al. (2021) for German. Thus, for applying UCTG to evaluate the uniform complexity of multilingual NLG systems, we still recommend going back to the basics, such as training models with linguistically plausible and domain-specific features as starting points.

6.3 Diversity in selecting the right text complexity metrics.

Finally, we emphasize that the method of benchmarking NLG systems with UCTG is not strictly prescriptive and linear as with other evaluation metrics used in text generation. The choice of selecting the appropriate combination of linguistic features to measure the complexity of machine-generated texts is suggestive and entirely up to the researcher’s judgment. For example, one may exclusively select vocabulary-based metrics deriving from psycholinguistic features similar to the ones reported in Table 8 for language learning tasks such as question generation as done in (Jiao et al., 2023). Moreover, a researcher can also train machine learning models from an extensive set of selected linguistic features as scorers of text complexity as done in Lee et al. (2021). The variety of candidate linguistic features may be selected with consideration of the domain of data used for training the generative models, its target users (as discussed previously), the language intricacies and properties of the data, and the extensiveness of the evaluation of said models.

7 Conclusion

In this study, we introduce Uniform Complexity for Text Generation (UCTG), a new benchmark task to encourage the production of uniformly complex generations with respect to prompts. To further ground the existence of the problem, we perform the most extensive investigation of linguistic properties (160 features) analyzed from generations of GPT-2 models for the narrative generation task. We find clear inconsistencies with the models, whether finetuned or not, in terms of preserving the text complexity of generations with respect to the prompts used. However, we do note some similarities in specific linguistic variables related to word familiarity and word use between humans and GPT-2 models in how they produce continuations to a prompt. Recognizing the potential and benefits of UCTG to increase the usability and accessibility of NLG systems, we discuss three major recommendations covering the importance of user background, language dependency, and flexibility of implementation if UCTG is to be implemented as an automatic evaluation metric or benchmark task for any arbitrary generative models from here onwards.

Limitations

We discuss clarifying statements below regarding the scope and limitations of this study.

On the specific use of GPT-2 models. While the possibility of using more advanced models such as GPT-4, and ChatGPT may come to one’s option for nearly all generative tasks, we emphasize that the availability of these models do not disregard the rich literature of narrative generation work using GPT-2. Likewise, models such as ChatGPT and GPT-4 cannot technically and freely be considered baseline models for comparison as the developers of these models provided limited transparency in their documentation and a paywall for their usage.

On proving the research problem exists. We emphasize that the goal of this study is to prove that the research problem, the challenge of maintaining the complexity of generated responses with respect to prompts, exists rather than proposing experimenting with a slew of controllability methods for LLMs without a proper in-depth grounding of the problem. Our empirical investigation makes use of a full linguistic analysis of prompt-continuation pairs from humans and neural language models. We explore methods such as fine-tuning as the standard way of calibrating LLMs. We show that this task may be complex in nature, and fine-tuning may not be a direct solution to the problem, thus an open research opportunity for researchers in the field to explore.

On experiments exclusively with English data. All experiments, findings, and insights in this work only apply to English, as evidenced by the language of the datasets used. Thus, our findings may not generalize if similar research derived from this work is to be done with other languages using other models, such as those trained with multilingual data.

On varying complexities with increasing length. Our experiments, particularly with the generation
setup as described in Section 3, focus on a specific limit of tokens (minimum 150 and maximum 300) for uniformity of analysis across models. The complexity of a text may not be directly linear when substantially longer passages are generated beyond our experimentation. We leave the fine-grained exploration of measuring complexities of text segments and chunks to future work.

On use of variables beyond linguistic features. Our experiments and findings specifically focus on possible inconsistencies found in texts generated by LLMs using linguistically motivated features such as vocabulary use, syntax, discourse, and part of speech. We note that there are other forms of analysis done previously using information theory concepts such as entropy and uniform information density principle on tasks such as dialogue-based data (Giulianelli and Fernández, 2021; Giulianelli et al., 2021). We currently have no proof of how these concepts relate or connect to inconsistencies associated with linguistic features but leave this to future work.

Ethics Statement

The datasets used, WRITINGPROMPTS, NEWSLELA, and ELG, are all available for researchers through the links provided, with some minor information needed to provide the purpose of use. In addition, we do not involve any human participants in this study as it is centered on text complexity which is an automatic evaluation by nature. Similar to the GPT-2 model finetuned by DeLucia et al. (2021), the GPT-2 model finetuned with uniformly written texts (NEWSLELA, ELG) has been made available in Huggingface.

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References

Sweta Agrawal and Marine Carpuat. 2019. Controlling text complexity in neural machine translation. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1549–1564, Hong Kong. China. Association for Computational Linguistics.

Nader Akoury, Shufan Wang, Josh Whiting, Stephen Hood, Nanyun Peng, and Mohit Iyyer. 2020. STORIUM: A Dataset and Evaluation Platform for Machine-in-the-Loop Story Generation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6470–6484, Online. Association for Computational Linguistics.

Santanjee Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Regina Barzilay and Mirella Lapata. 2008. Modeling local coherence: An entity-based approach. Computational Linguistics, 34(1):1–34.

Scott F Beers and William E Nagy. 2009. Syntactic complexity as a predictor of adolescent writing quality: Which measures? Which genre? Reading and Writing, 22(2):185–200.

Mark Breuker. 2022. CEFR Labelling and Assessment Services. In European Language Grid: A Language Technology Platform for Multilingual Europe, pages 277–282. Springer International Publishing.

Marc Brysbaert and Boris New. 2009. Moving beyond Kučera and Francis: A critical evaluation of current word frequency norms and the introduction of a new and improved word frequency measure for American English. Behavior Research Methods, 41(4):977–990.

Ozan Caglayan, Pranava Madhyastha, and Lucia Specia. 2020. Curious case of language generation evaluation metrics: A cautionary tale. In Proceedings of the 28th International Conference on Computational Linguistics, pages 2322–2328, Barcelona, Spain (Online). International Committee on Computational Linguistics.

John B Carroll. 1964. Language and Thought. Foundations of Modern Psychology Series.
Haw-Shiuan Chang, Jiaming Yuan, Mohit Iyyer, and Andrew McCallum. 2021. Changing the mind of transformers for topically-controllable language generation. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 2601–2611, Online. Association for Computational Linguistics.

Xiaobin Chen and Detmar Meurers. 2016. Characterizing text difficulty with word frequencies. In Proceedings of the 11th Workshop on Innovative Use of NLP for Building Educational Applications, pages 84–94, San Diego, CA. Association for Computational Linguistics.

Meri Coleman and Ta Lin Liau. 1975. A computer readability formula designed for machine scoring. *Journal of Applied Psychology, 60*(2):283.

Alexandra DeLucia, Aaron Mueller, Xiang Lisa Li, and João Sedoc. 2021. Decoding methods for neural narrative generation. In *Proceedings of the 1st Workshop on Natural Language Generation, Evaluation, and Metrics (GEM 2021)*, pages 166–185, Online. Association for Computational Linguistics.

William H DuBay. 2004. *The Principles of Readability*. Online Submission.

D Dugast. 1978. Sur quoi se fonde la notion d’étendue théoretique du vocabulaire? *Le Francais Moderne*, 46:25–32.

Angela Fan, Mike Lewis, and Yann Dauphin. 2018. Hierarchical neural story generation. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 889–898, Melbourne, Australia. Association for Computational Linguistics.

Lijun Feng, Noémie Elhadad, and Matt Huenerfauth. 2009. Cognitively motivated features for readability assessment. In *Proceedings of the 12th Conference of the European Chapter of the ACL (EACL 2009)*, pages 229–237, Athens, Greece. Association for Computational Linguistics.

Rudolph Flesch. 1948. A new readability yardstick. *Journal of Applied Psychology, 32*(3):221.

Irene C Fountas and Gay Su Pinnell. 1999. *Matching Books to Readers: Using Leveled Books in Graded Reading, K-3*. ERIC.

Thomas François and Eleni Miltsakaki. 2012. Do NLP and machine learning improve traditional readability formulas? In *Proceedings of the First Workshop on Predicting and Improving Text Readability for target reader populations*, pages 49–57, Montréal, Canada. Association for Computational Linguistics.

Sebastian Gehrmann, Tosin Adegum, Karmanya Aggarwal, Pawan Sasanka Ammanamanchi, Anuoluwapo Aremu, Antoine Bosselut, Khyathi Raghavi Chandu, Miruna-Adriana Clinciu, Dipanjan Das, Kaustubh Dhole, Wanyu Du, Esin Durmus, Ondřej Dušek, Chris Chinenyere Emezue, Varun Gangal, Cristina Garbaceva, Tatsunori Hashimoto, Yufang Hou, Yacine Jernite, Harsh Jhamtani, Yangfeng Ji, Shailza Jolly, Mihir Kale, Dhruv Kumar, Faisal Ladhak, Aman Madaan, Mounica Maddela, Khyati Mahajan, Saad Mahamood, Bodhisattwa Prasad Majumder, Pedro Henrique Martins, Angelina McMillan-Major, Simon Mille, Emiel van Miltenburg, Moin Nadeem, Shashi Narayan, Vitaly Nikolaev, Andre Niyongobo Rubungo, Salomey Osei, Ankur Parikh, Laura Perez-Beltrachini, Niranjan Ramesh Rao, Vikas Raunak, Juan Diego Rodriguez, Sashank Santhanam, Joao Sedoc, Thibault Sellam, Samira Shaikh, Anastasia Shimo-rina, Marco Antonio Sobrevilla Cabezudo, Hendrik Strobelt, Nishant Subramani, Wei Xu, Diyi Yang, Akhila Yerukola, and Jiawei Zhou. 2021. The GEM benchmark: Natural language generation, its evaluation and metrics. In *Proceedings of the 1st Workshop on Natural Language Generation, Evaluation, and Metrics (GEM 2021)*, pages 96–120, Online. Association for Computational Linguistics.

Dmitriy Genzel and Eugene Charlin. 2002. Entropy rate constancy in text. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 199–206, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Edward E Gickling and David L Armstrong. 1978. Levels of Instructional Difficulty as Related to On-task Behavior, Task Completion, and Comprehension. *Journal of Learning Disabilities, 11*(9):559–566.

Mario Giulianelli and Raquel Fernández. 2021. Analysing human strategies of information transmission as a function of discourse context. In *Proceedings of the 25th Conference on Computational Natural Language Learning*, pages 647–660, Online. Association for Computational Linguistics.

Mario Giulianelli, Arabella Sinclair, and Raquel Fernández. 2021. Is information density uniform in task-oriented dialogues? In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 8271–8283, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Sian Gooding, Ekaterina Kochmar, Seid Muhie Yimam, and Chris Biemann. 2021. Word complexity is in the eye of the beholder. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4439–4449, Online. Association for Computational Linguistics.

Sian Gooding and Manuel Tragut. 2022. One size does not fit all: The case for personalised word complexity models. In *Findings of the Association for Computational Linguistics: NAACL 2022*, pages 353–365, Seattle, United States. Association for Computational Linguistics.
Jian Guan and Minlie Huang. 2020. **UNION: An Unreferenced Metric for Evaluating Open-ended Story Generation.** In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9157–9166, Online. Association for Computational Linguistics.

Rowena C. Guevarra. 2011. **Development of a Filipino text readability index.**

Camille Guinaudeau and Michael Strube. 2013. **Graph-based local coherence modeling.** In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 93–103, Sofia, Bulgaria. Association for Computational Linguistics.

Robert Gunning et al. 1952. *Technique of Clear Writing.* McGraw-Hill.

Michael Heilman, Kevyn Collins-Thompson, Jamie Callan, and Maxine Eskenazi. 2007. Combining lexical and grammatical features to improve readability measures for first and second language texts. In *Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Proceedings of the Main Conference*, pages 460–467, Rochester, New York. Association for Computational Linguistics.

Gustav Herdan. 1960. *Type-token Mathematics: A Textbook of Mathematical Linguistics.* Mouton.

Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. 2020. **XTREME: A Massively Multilingual Multi-task Benchmark for Evaluating Cross-lingual Generalization.** In *International Conference on Machine Learning*, pages 4411–4421. PMLR.

Chieh-Yang Huang, Saniya Naphade, Kavya Laalasa Karanam, and Ting-Hao Kenneth Huang. 2023. Conveying the predicted future to users: A case study of story plot prediction. In *The AAAI-23 Workshop on Creative AI Across Modalities.*

Joseph Marvin Imperial and Ekaterina Kochmar. 2023. **Automatic Readability Assessment for Closely Related Languages.** In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 5371–5386, Toronto, Canada. Association for Computational Linguistics.

Joseph Marvin Imperial and Ethel Ong. 2021. **Diverse Linguistic Features for Assessing Reading Difficulty of Educational Filipino Texts.** In *29th International Conference on Computers in Education Conference, ICCE 2021*, pages 51–56. Asia-Pacific Society for Computers in Education.

Joseph Marvin Imperial, Lloyd Lois Antonie Reyes, Michael Antonio Ibanez, Ranz Sapinit, and Mohammed Hussien. 2022. **A baseline readability model for Cebuano.** In *Proceedings of the 17th Workshop on Innovative Use of NLP for Building Educational Applications (BEA 2022)*, pages 27–32, Seattle, Washington. Association for Computational Linguistics.

Ying Jiao, Kumar Shridhar, Peng Cui, Wangchunshu Zhou, and Minrinnah Sachan. 2023. **Automatic educational question generation with difficulty level controls.** In *International Conference on Artificial Intelligence in Education*, pages 476–488.

J Peter Kincaid, Robert P Fishburne Jr, Richard L Rogers, and Brad S Chissom. 1975. *Derivation Of New Readability Formulas (Automated Readability Index, Fog Count And Flesch Reading Ease Formula) For Navy Enlisted Personnel.* Technical report, Naval Technical Training Command Millington TN Research Branch.

George R Klare. 1974. **Assessing Readability.** *Reading Research Quarterly*, pages 62–102.

Kalpesh Krishna, John Wieting, and Mohit Iyyer. 2020. Reformulating unsupervised style transfer as paraphrase generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 737–762, Online. Association for Computational Linguistics.

Victor Kuperman, Hans Stadthagen-Gonzalez, and Marc Brysbaert. 2012. **Age-of-acquisition ratings for 30,000 English words.** *Behavior research methods, 44*(4):978–990.

Bruce W. Lee, Yoo Sung Jang, and Jason Lee. 2021. **Pushing on text readability assessment: A transformer meets handcrafted linguistic features.** In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 10669–10686, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Xiaofei Lu. 2012. **The Relationship of Lexical Richness to the Quality of ESL Learners’ Oral Narratives.** *The Modern Language Journal, 96*(2):190–208.

G Harry Mc Laughlin. 1969. **SMOG Grading - A New Readability Formula.** *Journal of reading, 12*(8):639–646.

Danielle S McNamara, Scott A Crossley, and Philip M McCarthy. 2010. **Linguistic Features of Writing Quality.** *Written communication, 27*(1):57–86.

Jekaterina Novikova, Ondřej Dušek, Amanda Cercas Curry, and Verena Rieser. 2017. Why we need new evaluation metrics for NLG. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2241–2252, Copenhagen, Denmark. Association for Computational Linguistics.

Kieran O’Loughlin. 1995. **Lexical density in candidate output on direct and semi-direct versions of an oral proficiency test.** *Language Testing, 12*(2):217–237.
Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Edoardo Maria Ponti, Goran Glavaš, Olga Majewska, Qianchu Liu, Ivan Vulić, and Anna Korhonen. 2020. XCOPA: A multilingual dataset for causal common-sense reasoning. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2362–2376, Online. Association for Computational Linguistics.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language Models are Unsupervised Multitask Learners. OpenAI Blog, 1(8):9.

Ehud Reiter and Anja Belz. 2009. An investigation into the validity of some metrics for automatically evaluating natural language generation systems. Computational Linguistics, 35(4):529–558.

Melissa Roemmele. 2021. Inspiration through Observation: Demonstrating the Influence of Generated Text on Creative Writing. arXiv preprint arXiv:2107.04007.

Melissa Roemmele, Andrew S Gordon, and Reid Swanson. 2017. Evaluating Story Generation Systems Using Automated Linguistic Analyses. In SIGKDD 2017 Workshop on Machine Learning for Creativity, pages 13–17.

Ananya B. Sai, Tanay Dixit, Dev Yashpal Sheth, Sreyas Mohan, and Mitesh M. Khapra. 2021. Perturbation CheckLists for evaluating NLG evaluation metrics. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 7219–7234, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Carolina Scarton, Gustavo Paetzold, and Lucia Specia. 2018. Text Simplification from Professionally Produced Corpora. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018), Miyazaki, Japan. European Language Resources Association (ELRA).

Sarah Schwarm and Mari Ostendorf. 2005. Reading level assessment using support vector machines and statistical language models. In Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL ’05), pages 523–530, Ann Arbor, Michigan. Association for Computational Linguistics.

Abigail See, Aneesh Pappu, Rohun Saxena, Akhila Yerukola, and Christopher D. Manning. 2019. Do massively pretrained language models make better storytellers? In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL), pages 843–861, Hong Kong, China. Association for Computational Linguistics.

Edgar A Smith and RJ Senter. 1967. Automated readability index, volume 66. Aerospace Medical Research Laboratories, Aerospace Medical Division.

Amanda Stent, Matthew Marge, and Mohit Singhai. 2005. Evaluating Evaluation Methods for Generation in the Presence of Variation. In CICLing, volume 2005, pages 341–351. Springer.

Simeng Sun, Kalpesh Krishna, Andrew Mattarella-Micke, and Mohit Iyyer. 2021. Do long-range language models actually use long-range context? In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 807–822, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Edward Lee Thormidke. 1927. The teacher’s word book. Teachers College, Columbia University.

Fiona J Tweedie and R Harald Baayen. 1998. How Variable May a Constant Be? Measures of Lexical Richness in Perspective. Computers and the Humanities, 32(5):323–352.

Sowmya Vajjala and Detmar Meurers. 2016. Readability-Based Sentence Ranking for Evaluating Text Simplification. arXiv preprint arXiv:1603.06009.

Zarah Weiss, Xiaobin Chen, and Detmar Meurers. 2021. Using Broad Linguistic Complexity Modeling for Cross-Lingual Readability Assessment. In Proceedings of the 10th Workshop on NLP for Computer Assisted Language Learning, pages 38–54, Online. LiU Electronic Press.

Bernard L Welch. 1947. The Generalization of STUDENT’S Problem When Several Different Population Variances Are Involved. Biometrika, 34(1-2):28–35.

Sam Witteveen and Martin Andrews. 2019. Paraphrasing with large language models. In Proceedings of the 3rd Workshop on Neural Generation and Translation, pages 215–220, Hong Kong. Association for Computational Linguistics.

Peng Xu, Mostofa Patwary, Mohammad Shoeybi, Raul Puri, Pascale Fung, Anima Anandkumar, and Bryan Catanzaro. 2020. MEGATRON-CNTRL: Controllable story generation with external knowledge using large-scale language models. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2831–2845, Online. Association for Computational Linguistics.

Wei Xu, Chris Callison-Burch, and Courtney Naples. 2015. Problems in current text simplification research: New data can help. Transactions of the Association for Computational Linguistics, 3:283–297.
Wei Xu, Courtney Napoles, Ellie Pavlick, Quanze Chen, and Chris Callison-Burch. 2016. Optimizing statistical machine translation for text simplification. Transactions of the Association for Computational Linguistics, 4:401–415.

Zhexin Zhang, Jiaxin Wen, Jian Guan, and Minlie Huang. 2022. Persona-guided planning for controlling the protagonist’s persona in story generation. In Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3346–3361, Seattle, United States. Association for Computational Linguistics.

A Uniform Barplot Visualization per Linguistic Feature
| Feature                        | Data Points | Sentiment | Tokenization | Corpora |
|-------------------------------|-------------|-----------|--------------|---------|
| SubtlexUS SUBTL sent          |             |           |              |         |
| SubtlexUS SUBTL token         |             |           |              |         |
| SubtlexUS sent                |             |           |              |         |
| SubtlexUS token               |             |           |              |         |
| Total token x Total sent      |             |           |              |         |
| Uber Index                    |             |           |              |         |
| Verb POS to Adj POS          |             |           |              |         |
| Verb POS to Adv POS          |             |           |              |         |
| Verb POS to CordConj         |             |           |              |         |
| Verb POS to Noun POS         |             |           |              |         |
| Verb POS to SubrdConj        |             |           |              |         |
| Verb phrs to Adj phrs        |             |           |              |         |
| Verb phrs to Adv phrs        |             |           |              |         |
| Verb phrs to Noun phrs       |             |           |              |         |
| Verb phrs to Prep phrs       |             |           |              |         |
| Verb phrs to SubClaus        |             |           |              |         |