

The Perils of Using Mechanical Turk to Evaluate Open-Ended Text Generation

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Abstract

Recent text generation research has increasingly focused on open-ended domains such as story and poetry generation. Because models built for such tasks are difficult to evaluate automatically, most researchers in the space justify their modeling choices by collecting crowdsourced human judgments of text quality (e.g., Likert scores of coherence or grammaticality) from Amazon Mechanical Turk (AMT). In this paper, we first conduct a survey of 45 open-ended text generation papers and find that the vast majority of them fail to report crucial details about their AMT tasks, hindering reproducibility. We then run a series of story evaluation experiments with both AMT workers and English teachers and discover that even with strict qualification filters, AMT workers (unlike teachers) fail to distinguish between model-generated text and human-generated references. We show that AMT worker judgments improve when they are shown model-generated output alongside human-generated references, which enables the workers to better calibrate their ratings. Finally, interviews with the English teachers provide deeper insights into the challenges of the evaluation process, particularly when rating model-generated text.

1 Introduction

Recent advances in neural language modeling have spurred research into open-ended text generation tasks such as story generation (Peng et al., 2018a), style transfer (Krishna et al., 2020), and pun generation (He et al., 2019). Since the space of possible outputs for these tasks is huge compared to more constrained problems such as machine translation, automatic metrics such as BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004) that measure similarity to reference texts are mostly uninformative (Akoury et al., 2020).¹ Human evaluation of

¹Nevertheless, such metrics are commonly reported in research papers on open-ended text generation.

model-generated text, which is critical for open-ended tasks given the unreliability of automatic metrics (Peng et al., 2017; Reiter, 2018; See et al., 2019), is frequently conducted on Amazon’s popular Mechanical Turk platform (AMT) to minimize cost and time. Most existing AMT studies ask crowdworkers to provide Likert scale ratings of various properties of generated text, such as *fluency* and *likability*.

In this paper, we study the reliability and reproducibility of AMT evaluations of open-ended text generation. We first conduct a survey of papers on open-ended text generation between 2018-2020 and find many critical details often go unreported (e.g., worker qualifications, payment, task descriptions, annotator agreement), a finding in line with prior reproducibility studies outside open-ended text generation (Card et al., 2020; Howcroft et al., 2020; van der Lee et al., 2021).

Next, we perform a series of story generation evaluations with both AMT workers and expert raters (English teachers), applying a variant of the most common task configuration that appeared in our survey (5 point Likert scale ratings of 200 examples with three annotators per example) to the paragraph-length `WritingPrompts` dataset of Fan et al. (2018). Unlike prior work in this area, we ask raters to evaluate both stories generated by a fine-tuned GPT-2 language model (Radford et al., 2019) and *human-written reference* stories on the same scale, as we expect the latter to consistently score higher on all evaluations. Our experiments expose and quantify several troubling trends:

1. AMT ratings do not reliably distinguish model-generated text from human-generated text unless workers are asked to rate both side-by-side, which allows them to better calibrate their ratings.
2. Running an identical task (same AMT parameters and input data) on different days of the

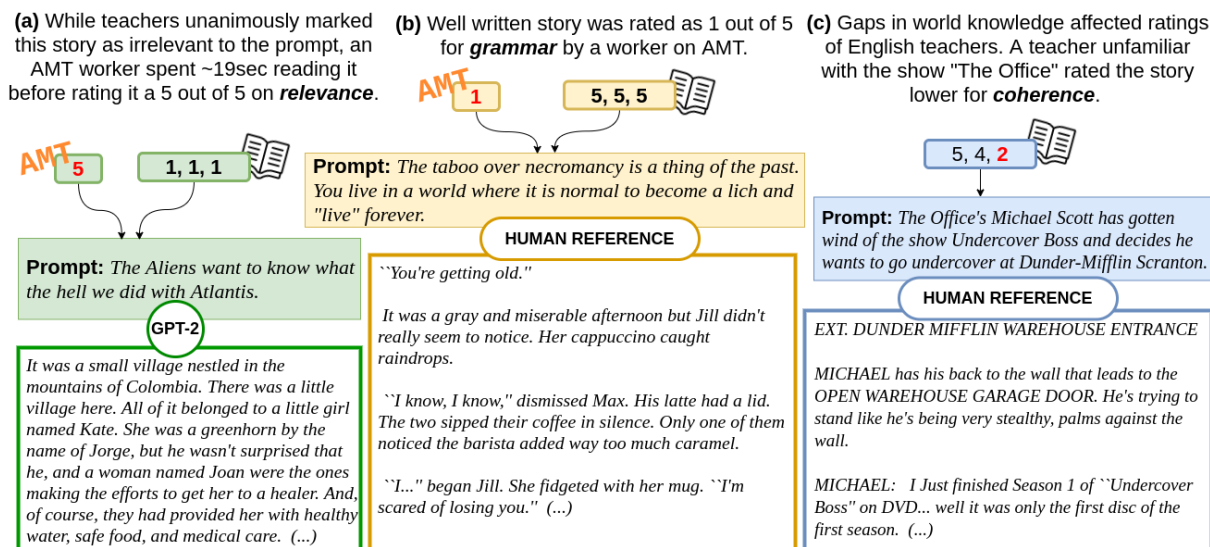


Figure 1: Three examples of prompt-story pairs along with ratings from AMT workers and expert teachers that demonstrate major issues with human evaluation of open-ended text generation.

- week exhibits high variance and can lead to dubious conclusions (e.g., that reference texts are lower quality than GPT-2 generated text).
3. Many AMT workers do not carefully read the text that they are evaluating. Even after enabling multiple qualifications to exclude low-quality workers, 42% of workers on average take fewer than 40 seconds to complete each task. Filtering out these workers can make a significant impact to the overall ratings, but also notably reduces the number of datapoints.
 4. Even expert raters struggle to read and judge model-generated text. The time they spend per example increases significantly compared to that for references, and agreement also drops.

For future human evaluations of open-ended text generation tasks, we urge researchers to obtain expert raters whenever possible. If AMT is the only feasible option, we recommend that available reference outputs also be evaluated alongside model-generated ones to improve rating calibration, and also that heavy filtering of the worker population (possibly through qualification tasks, or post-hoc removal) is performed prior to reporting results.

2 A survey of papers that evaluate open-ended text generation with AMT

We begin with a survey of 45 papers that use AMT to evaluate the output of open-ended English-language text generation models, which includes

generated stories, metaphors, paraphrases, puns, sarcasm, and sentences with transferred style or attributes². Each paper was published between 2018 and 2020 at ACL, NAACL, or EMNLP, and we exclude papers that use AMT to evaluate more well-established generation tasks like machine translation, or summarization.³ Unlike previous surveys of evaluating generated text (Çelikyilmaz et al., 2020; van der Lee et al., 2021), we focus specifically on AMT evaluations of open-ended text generation. In this section, we provide an overview of the different types of evaluation task setups present in our survey; later, we experiment with several variants of the most common setup.

Evaluation criteria: As in the survey of Howcroft et al. (2020), we observe a variety of different evaluation criteria and definitions of these criteria across the 45 papers. The most common criteria include *fluency* and/or *grammaticality* (19), *overall "quality"* (12), and *relevance* (10) to a corresponding prompt. Furthermore, stories in particular tend to also be evaluated on some notion of *coherence* (9) and *likability* (4).

²The details on the survey questions and surveyed papers are provided in the Appendix A

³For detailed numbers see Table A1; the specific papers in the survey are in Table A2. Four papers conducted multiple evaluations with different settings, and as such we count them in multiple categories. Moreover, all but nine papers evaluated their systems on more than one attribute.

Rating scales: More than half of the papers (24) employ a 5-point Likert scale to evaluate the above criteria; of these, 19 provided labels for just the end points of the scale (e.g., “lowest” vs. “highest”), while 5 labeled all points on the scale. The next most common evaluation type is ranking two or more system outputs (23). Less common are other Likert scales (3, 4, or 6-point), pass/fail tasks, and output-prompt matching tasks.

Number of raters and rated items: An alarming number of papers (14) do not even report the number of raters and/or items (6) used for evaluation. Of the remaining, most papers (16) obtain ratings from 3 separate AMT workers per item. The most common number of items per evaluation is 100 (14). The number of raters per item in other studies ranges from 2 to 11, while the number of items ranges from 12 to 1,000.

Workers qualifications and compensation: The vast majority of papers do not report AMT worker qualifications (32) or worker compensation (35), which adds to the reproducibility woes. Among papers that report qualifications, the most common were HIT⁴ approval rate $\geq 90\%$ -99%, and number of approved HITs between 500 to 5,000. Only 11 papers mentioned restricting workers to those from English-speaking countries or applying some kind of language test, despite all evaluations being done on English text.

Length of the Rated Text: As open-ended text generation encompasses an array of different tasks, the length of the rated text differed greatly, ranging from single sentences (28), sometimes presented in a longer context, to short paragraphs (7), and longer paragraphs (14). The latter setting is most commonly used for story generation tasks.

3 Evaluating story generation with AMT

Our survey reveals that the most popular Mechanical Turk task design for open-ended text generation asks AMT workers to rate various properties of generated text on a 5-point Likert scale. In this section, we conduct a series of AMT evaluations for the open-ended problem of *story generation* by varying different parameters within this standard task design. Importantly, we evaluate both model-generated stories as well as *human-generated refer-*

ence stories, which provides a pseudo upper bound for the ratings. Our experiments reveal that worker qualifications (e.g., HIT approval rate and number of accepted HITs) do not notably impact judgments or spam rate on reference stories, with the exception of country of origin. Furthermore, we uncover an issue with *rating calibration*: when both reference and model-generated stories are included for the same prompt, average reference scores are significantly higher than those for model-generated text; however, when workers only see one type of text per HIT, they give similar average scores to both types.

3.1 Experimental Setup

We first describe the parameters of our experiments before later analyzing the results.

Dataset: We use the `WritingPrompts` dataset collected by Fan et al. (2018), which is a collection of 303,358 English language stories written by Reddit users on the `r/WritingPrompts` subreddit.⁵ This dataset, which consists of short prompts paired with user-written stories (e.g., “There are 10 legendary dentists who review every toothpaste. You are the 10th... being hunted by the other 9...”), has been used in multiple previous works on paragraph-length story generation (Fan et al., 2019; See et al., 2019; Mao et al., 2019). We randomly select 200 prompts from the test set for all of our experiments. Since the human-written stories in the dataset are already tokenized, we first de-tokenized the stories, cleaned up artifacts from lemmatization, and manually truncated each story so that it ends with a full sentence and is no longer than 150 words in order to make the length comparable with the machine-generated story.⁶ We use the resulting stories for all experiments with reference text.

Model-generated stories: We follow a similar modeling approach to prior story generation work (Mao et al., 2019; Guan et al., 2020) by fine-tuning a pretrained GPT-2 medium-sized model (Radford et al., 2019) on the training set of the `WritingPrompts` dataset, using the HuggingFace Transformers library (Wolf et al., 2020). We use a batch size of approximately 50k tokens, a learning rate of $5e - 5$ with a linear learning rate schedule, and train for 3 epochs, stopping training

⁴In AMT parlance, a human intelligence task (HIT) refers to a single item; in our case, each HIT corresponds to one story, which workers rate on four different properties.

⁵<https://reddit.com/r/WritingPrompts/>
⁶The mean length of the selected reference stories is 134.5 tokens, with a standard deviation of 8.81.

after validation perplexity converges to ~ 19 . Each training example consists of a concatenation of a prompt, separator token (new line character), and reference story. At test-time, we feed the same 200 prompts selected above to our model for fair comparison to the human-written stories, and we generate three stories per prompt using nucleus sampling (Holtzman et al., 2019) with $p = 0.9$. We manually truncate each sample so that it ends with a full sentence and is no longer than 150 words.⁷ These stories are used in all experiments evaluating machine-generated stories.

AMT task parameters: We conduct all experiments using the default interface in Mechanical Turk (see Figure A1 and Figure A2). Workers were asked to rate human-written and/or machine-generated stories on four attributes, with the following definitions provided to them:

1. *Grammar*: “How grammatically correct is the text of the story fragment?”
2. *Coherence*: “How well do the sentences in the story fragment fit together?”
3. *Likability*: “How enjoyable do you find the story fragment?”
4. *Relevance*: “How relevant is the story fragment to the prompt?”

Their ratings fall on a 5-point Likert scale with the corresponding endpoints labelled as “lowest” (1 point) and “highest” (5 points). Since our survey did not find many previous papers that reported using detailed descriptions for each point on the scale, we chose to use minimal labels to mimic the most popular setup (see Section 2 for details).

Each of our AMT experiments shows workers the same 200 prompts paired with human and/or machine-generated stories, and we solicit three worker judgments per HIT. Workers were paid \$0.20 per HIT for tasks that showed one story, and \$0.35 per HIT for those that showed two stories; in total, our AMT experiments cost roughly \$1.5K. Importantly, each experiment used a completely different set of workers (i.e., each worker could only participate in one experiment, although they can complete multiple HITs within that experiment), which is an intentional choice to prevent workers from judging the same story multiple times. Finally, to eliminate potential variations stemming

⁷The mean length of the generated stories is 137.4 tokens, with a standard deviation of 8.36.

from evaluation on different days (weekdays vs. weekends) and time of day, we launch all experiments on weekdays between 11:00-11:30AM PST.

3.2 AMT Evaluations of Reference Text

Our first set of experiments concerns only human-written reference stories; we move to machine-generated text in the next subsection. One of our assumptions with human-written stories, supported by the expert teacher assessment in Section 4, is that they should receive relatively high scores for all four properties (except perhaps *likability* which is highly subjective). We thus use reference texts to evaluate various AMT parameters such as qualifications or day of task launch, observing how modifications to these parameters affect the average scores of reference text.

Impact of worker qualifications: We run four experiments evaluating the previously-described set of 200 prompts with reference story fragments, varying the worker qualifications as follows: (1) no qualifications, (2) including only workers with HIT approval rate $> 90\%$, (3) including only workers with approval rate $> 90\%$ and at least 1000 approved HITs, (4) including only workers with approval rate $> 90\%$ and at least 1000 approved HITs who are located in English-speaking countries.⁸

The results in the top portion of Table 1 suggest that applying all of the qualifications (i.e., workers from English-speaking countries, approval rate $> 90\%$, approved HITs ≥ 1000) has a positive effect on the quality of workers, as this setting yielded the highest scores out of the four experiments for *coherence* and *relevance* while ratings for *grammar* were also considerably high. Ratings for *likability* were lower than in the experiments with less strict qualifications, but *likability* is a very subjective measure which consistently shows a very low agreement (Krippendorff’s α of -0.04 to 0.11). When all AMT worker qualifications are enabled, the worker ratings more closely align to those made by English teachers, although there are still substantial deviations (Section 4). Additionally, with all qualifications enabled, workers show higher agreement for *grammar*, *coherence*, *relevance* and even *likability*, although the agreement between raters remains low.

High variance across different days: Concerned by the low overall agreement, we decided

⁸We include workers from the US, Canada, the UK, Australia, and New Zealand.

Experiment description	Grammar		Coherence		Relevance		Likability	
	Mean _{STD}	IAA%	Mean _{STD}	IAA%	Mean _{STD}	IAA%	Mean _{STD}	IAA%
<i>Impact of Qualifications</i>								
No qualifications	4.05 _{0.90}	0.08 _{14.5}	3.92 _{0.98}	0.02 _{4.5}	3.66 _{1.22}	0.13 ₁₁	3.64 _{1.16}	0.02 ₇
+ > 90% HIT approval	4.16 _{0.86}	0.07 ₁₈	4.07 _{0.93}	0.06 _{10.5}	3.67 _{1.14}	0.07 ₉	3.68 _{1.15}	0.08 ₁₀
+ at least 1000 HITs	3.91 _{0.85}	0.05 ₁₂	3.85 _{0.98}	0.08 _{11.5}	3.60 _{1.15}	0.18 ₈	3.63 _{1.13}	0.07 _{12.5}
+ English-speaking countries	4.00 _{0.92}	0.21 _{15.5}	4.11 _{0.96}	0.14 _{16.5}	3.71 _{1.26}	0.27 ₁₀	3.37 _{1.18}	0.11 _{7.5}
<i>Variance Across Days</i>								
Day 1 (all quals.)	4.00 _{0.92}	0.21 _{15.5}	4.11 _{0.96}	0.14 _{16.5}	3.71 _{1.26}	0.27 ₁₀	3.37 _{1.18}	0.11 _{7.5}
Day 2 (all quals.)	3.86 _{0.92}	-0.03 _{10.5}	3.92 _{0.98}	-0.03 _{6.5}	3.71 _{1.08}	0.02 ₁₁	3.73 _{0.97}	-0.04 _{8.5}
Day 3 (all quals.)	3.98 _{0.96}	0.18 ₁₁	4.05 _{0.94}	0.13 _{10.5}	3.46 _{1.29}	0.26 ₈	3.42 _{1.16}	0.07 _{4.5}
<i>Impact of Country of Origin</i>								
- English-speaking countries	3.82 _{1.04}	0.03 ₁₁	3.45 _{1.19}	-0.01 ₉	3.25 _{1.27}	0.03 _{6.5}	3.32 _{1.26}	-0.09 ₃
<i>Impact of Filtering by the Median Work Time</i>								
Day 2 (Median \geq 40s)	4.04 _{0.94}		4.33 _{0.92}		3.74 _{1.34}		3.67 _{1.06}	

Table 1: AMT experiments on human-written reference stories. Inter-annotator agreement (IAA) between the three raters is measured with Krippendorff’s α as well as the percentage of stories for which all three raters exactly agreed on a rating (the latter is subscripted). Last section omits IAA due to the large number of missing datapoints. Statistical significance for the relations between groups is provided in [Appendix D](#).

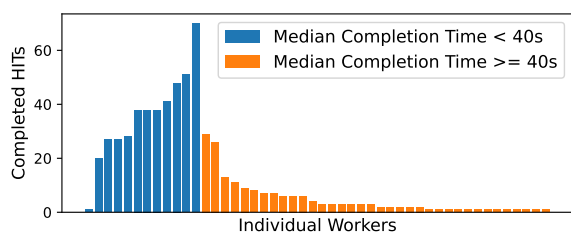


Figure 2: This example from Day 2 shows that many AMT workers complete multiple HITs in less time and with lower agreement in comparison to our experts.

to run another set of experiments that repeats the same experiment (all qualifications enabled) across three different days. Due to our constraint that each worker can only participate in one experiment, each of these experiments has a different subset of qualified workers. As shown in the second portion of [Table 1](#), although the first and third days yielded similar mean ratings/agreement in terms of *grammar* (M=4.00, IAA=0.21 vs M=3.98, IAA=0.18) and *coherence* (M=4.11, IAA=0.14 vs M=4.05, IAA=0.13), the second day received lower ratings across the board and had overall poor IAA (see [Table 1](#)). Furthermore, ratings for *relevance* in the third day (M=3.46) were significantly lower than in the first two days (M=3.71), which indicates that simply using all AMT qualifications is not enough to achieve consistent results.

Many AMT workers do not spend enough time reading the stories: The low overall agreement

also motivated us to examine the average time each worker spent per HIT. While AMT reports *WorkTimeInSeconds* in the results file made available to task requesters, we observe similar to [Akoury et al. \(2020\)](#) that these times are artificially inflated due to workers who accept multiple HITs at the same time and work on them sequentially (e.g., in different tabs). Such workers are also frequently among the most prolific in terms of HITs completed per experiment (see [Figure 2](#)), since there is no maximum number of HITs per worker.⁹ We correct for this by measuring the time between consecutively submitted HITs by the same worker, which can be derived by analyzing start and end times of each HIT. This “actual time” differs considerably from the AMT reported *WorkTimeInSeconds*: for instance, a worker that AMT reports had a mean work-time of 360 seconds had an actual mean working time¹⁰ of 22s and a median of 13s. To put these numbers in perspective, this is about one-fourth of the time that the fastest English teacher achieved (see [Section 4](#)).

As it is impossible to carefully read a paragraph-length story and assess all four properties in as little as 13 seconds, we measure the impact on average

⁹Like most AMT tasks ([Fort et al., 2011](#); [Robinson et al., 2019](#)), the majority of HITs for our evaluations are provided by a small fraction of workers. The majority of workers provided ratings for only one or two stories while a very few productive workers rated over 50% of the stories (see [Figure 2](#)).

¹⁰The mean work time is also not very representative as workers typically accept multiple HITs, wait a period of time, then submit all accepted HITs in quick succession.

ratings when filtering out workers who spend too little time per HIT (last row of Table 1). Specifically, we remove judgments from workers whose median time is below 40s (which is a low bar), and find that on average about 42% of our ratings are filtered out (ranging from 20%-72% across all experiments).¹¹ Of our surveyed papers, only Akoury et al. (2020) report actual work time, demonstrating that this is a major issue in modern AMT evaluations of text quality that most researchers have overlooked.

Impact of worker country of origin: While all of the surveyed papers evaluate only English text, only 11 of them reported using some kind of filtering to ensure that workers have sufficient knowledge of English. The default AMT setting does not filter workers by country of origin, which potentially increases the variance of results depending on the English proficiency of workers who accept HITs. To measure this, we re-run our experiment with all qualifications, except we restrict the task to only workers from countries that do not primarily speak English (i.e., we *exclude* workers from the US, Canada, UK, Australia, New Zealand, Ireland, and Singapore). The third portion of Table 1 shows that workers from non-English speaking countries rated *coherence*, *relevance*, and *grammar*¹² significantly lower than identically-qualified workers from English-speaking countries (Day 1-3). Thus, researchers rating English text should restrict their tasks to English-speaking countries, although Kennedy et al. (2020) find that many workers use Virtual Private Networks (VPNs) to take part in tasks restricted to those in the US.

3.3 Evaluating Machine-Generated Text

We now turn to AMT evaluation of machine-generated stories produced by the GPT-2 model described in subsection 3.1. Based on our previous experiments with reference texts, we select the “all qualifications” setting (i.e., workers from English-speaking countries, approval rate > 90%, approved HITs \geq 1000) for all GPT-2 AMT tasks. We study

¹¹We also ran experiments with even stricter qualification filters (i.e., acceptance rate \geq 99% and at least 10,000 approved tasks), but this made no notable difference to the percentage of data being filtered out (35%). This is most likely due to the fact that most requesters are reluctant to reject HITs regardless of quality, which results in an estimated 95% of workers having an approval rate of 98% or above (Matherly, 2019; Wessling et al., 2017).

¹²There was no significant difference between *grammar* ratings collected from raters from non-English speaking countries and ratings collected on Day 2.

two different conditions: (1) HITs contain a prompt and a GPT-2 generated text, and (2) HITs contain a prompt and both a human-written reference story as well as a GPT-2 generated story. In the latter case, we ask AMT workers to rate both texts on each of the four properties. Overall, we observe that workers cannot effectively distinguish between reference and model-generated stories when they are evaluated separately (in terms of average ratings), but that this distinction emerges clearly when they are presented with both types of stories in the same HIT.

When presented only GPT-2 generated text, AMT worker ratings rate them similarly to reference texts, despite obviously worse quality:

In our first experiment, we follow the protocol from our experiments with human-written reference stories, showing AMT workers a prompt and a model-generated story and asking them to rate it on the same attributes (*grammar*, *coherence*, *relevance*, and *likability*). The results of this evaluation are presented in the upper row of Table 2 along with the three sets of ratings of reference stories obtained with the same “all qualifications” setting from before (Days 1-3 in Table 1).

Surprisingly, GPT-2 output is *not* consistently rated significantly lower than human-written text. For instance, workers in Day 2 rated human-written stories similarly to the GPT-2 generated stories in terms of *grammar* (M=3.86 vs. M=3.94) and *coherence* (M=3.92 vs. M=3.82), while workers in Day 3 rated human-written stories as similarly *relevant* to the prompt as GPT-2 output (M=3.46 vs. M=3.44). Depending on which reference day we compare the GPT-2 output to, GPT-2 is rated similarly to human-written stories in terms of all four properties, which indicates that this evaluation is uninformative; nevertheless, the majority of surveyed papers use exactly this task design to obtain ratings for model-generated output.

Asking workers to rate both human-written and model-generated stories side-by-side improves ratings:

We hypothesize that the previous result is due to scale calibration differences between the two settings: when repeatedly confronted with incoherent model-generated text, a worker may be more generous with their ratings compared to if they only see coherent human-written text. Thus, we explore whether their ratings can be better calibrated by asking them to rate both types of

Raters	Type of text	Grammar		Coherence		Relevance		Likability	
		Mean _{STD}	IAA%	Mean _{STD}	IAA%	Mean _{STD}	IAA%	Mean _{STD}	IAA%
<i>AMT workers fail to effectively distinguish between human written and GPT-2 generated stories</i>									
AMT	Ref. (Day 1)	4.00 _{0.92}	0.21 _{15.5}	4.11 _{0.96}	0.14 _{16.5}	3.71 _{1.26}	0.27 ₁₀	3.37 _{1.18}	0.11 _{7.5}
AMT	Ref. (Day 2)	3.86 _{0.92}	-0.03 _{10.5}	3.92 _{0.98}	-0.03 _{6.5}	3.71 _{1.08}	0.02 ₁₁	3.73 _{0.97}	-0.04 _{8.5}
AMT	Ref. (Day 3)	3.98 _{0.96}	0.18 ₁₁	4.05 _{0.94}	0.13 _{10.5}	3.46 _{1.29}	0.26 ₈	3.42 _{1.16}	0.07 _{4.5}
AMT	GPT-2	3.94 _{0.93}	0.11 _{17.5}	3.82 _{1.12}	0.05 _{7.5}	3.44 _{1.41}	0.10 ₇	3.42 _{1.25}	0.02 _{4.5}
<i>AMT workers score GPT-2 lower when also presented with reference text</i>									
AMT	Reference	3.83 _{0.99}	0.13 _{12.5}	3.83 _{1.1}	0.07 ₈	3.49 _{1.26}	0.20 ₈	3.48 _{1.08}	0.03 _{6.5}
AMT	GPT-2	3.82 _{0.90}	0.10 ₁₂	3.39 _{1.1}	0.04 _{9.5}	2.70 _{1.26}	0.06 _{6.5}	2.99 _{1.14}	-0.04 ₄
<i>Teachers rate GPT-2 generated stories lower than AMT workers</i>									
Teachers	Reference	4.50 _{0.83}	0.19 _{35.5}	4.38 _{0.91}	0.14 ₂₅	3.82 _{1.38}	0.25 ₁₆	3.69 _{1.30}	-0.01 ₅
Teachers	GPT-2	4.56 _{0.62}	0.00 _{24.5}	3.73 _{1.19}	0.17 ₁₃	2.54 _{1.49}	0.54 _{25.5}	2.96 _{1.46}	-0.07 ₃

Table 2: Comparison of AMT workers and expert teachers on both human and machine-generated text. Inter-annotator agreement (IAA) between the three raters is measured with Krippendorff’s α as well as the percentage of stories for which all three raters exactly agreed on a rating (the latter is subscripted). Statistical significance for the relations between groups is provided in [Appendix C](#) and [Appendix D](#).

stories side-by-side, using the same qualification settings as for the other experiments. The results of this experiment are presented in the middle row of [Table 2](#). Workers score GPT-2 generated stories significantly lower than reference stories on *coherence* (M=3.39 vs. M=3.83), *relevance* (M=2.70 vs. M=3.49), and *likability* (M=2.99 vs. M=3.48), which is in line with our expectations. Their ratings for *grammar* (M=3.82 vs. M=3.83) are similar for both types of text, which we also observe with expert teacher ratings in [Section 4](#) and is expected since GPT-2’s output is generally grammatical.

4 Evaluation by expert teachers

The experiments in the previous section demonstrate the unreliability of AMT ratings for open-ended text generation, even when qualifications are used to restrict the task to ostensibly reliable workers. In this section, we compare the ratings produced by AMT workers to those of expert raters, specifically a set of three English teachers, and discover significant deviations between the two groups. Though they rated both types of stories separately, their ratings clearly distinguish between human-written references and machine-generated stories. We also conducted post-task interviews with the teachers and organized a mediation session to discuss stories with high disagreement, observing that they reach consensus after discussion in about 80% of cases.

Recruiting English teachers: We choose English teachers as experts for our story generation task because they regularly evaluate student-written

papers and are experienced at detecting both low-level grammatical mistakes as well as discourse-level issues with logical coherence. The three teachers were recruited from the authors’ personal networks, and each of them either has a degree in teaching English as a Second Language or a CELTA certificate.¹³ They were paid \$125 each for participating in our experiments, which required them to rate the same 200 human-written stories and 200 GPT-2 generated stories on the same four properties as that of the AMT workers, given an identical task interface.¹⁴

Unlike AMT workers, teachers rate reference stories higher than GPT-2 generated ones: We asked teachers to first rate the 200 reference stories, and then a week later to rate the GPT-2 generated stories. Just like the AMT workers, they were not told that the text in the second task was machine-generated. Importantly, we used the same set of teachers for both tasks, so they already had significant experience with the task when rating the machine-generated text (as opposed to using new AMT workers for each experiment).

The results of this evaluation are presented in the last row of [Table 2](#). Unsurprisingly, teachers rated human-written stories significantly higher than GPT-2 generated stories in terms of *coherence* (M=4.38 vs. M=3.73), *relevance* (M=3.82 vs. M=2.54), and *likability* (M=3.69 vs. M=2.96) (all

¹³Certificate in Teaching English to Speakers of Other Languages.

¹⁴The teachers completed their ratings using an identical version of our task deployed on the AMT sandbox environment.

p 's<0.001). On the other hand, they rated human-written stories and GPT-2 generated stories as similar in terms of *grammar* ($M=4.50$ vs. $M=4.56$). Moreover, teachers' ratings of human-written stories are considerably higher than AMT ratings for all attributes except *likability* ($M=3.69$) which depending on the day was rated lower ($M_{\text{Day1}}=3.37$) or higher ($M_{\text{Day2}}=3.73$) by the AMT workers. Similarly, teachers' ratings of GPT-2 stories are lower than the ratings we obtained from AMT workers for *coherence* ($M=3.73$ vs. $M=4.11$), *relevance* ($M=2.54$ vs. $M=3.71$), and *likability* ($M=2.96$ vs. $M=3.37$).

Teachers need to see many examples to properly calibrate their ratings: In post-task interviews, all teachers reported that it took them 10-20 stories on average to calibrate their ratings. Since most AMT workers complete only one to two HITs, they do not have similar time to get acquainted with the task; this may suggest that having a pre-task training phase can improve worker calibration.

Coherence is difficult to rate for machine-generated text: The teachers unanimously report that while *coherence* is easy to rate for reference stories (since most of them are largely coherent), it is the most difficult property to rate for GPT-2 generated stories. Since they did not know that they were rating machine-generated text, they spent time trying to make sense of the author's possible intent in producing many of the strange artifacts and hallucinations common to output of neural language models (Holtzman et al., 2019). In contrast, *relevance* turned out to be the easiest property of machine-generated text for teachers to rate, which is expected as many of GPT-2's stories deviate very quickly from the prompt (see Figure 1).

GPT-2 generated stories are much harder for teachers to rate overall: All teachers reported struggling more when rating GPT-2 stories, a fact reflected in their average rating time per story increasing significantly from 69.8 seconds to 87.3 seconds ($p<0.05$). In contrast, the average rating time of AMT workers *decreased* from 135.3 seconds for human-written text (Day 1) to 91.5 seconds for GPT-2 text ($p<0.05$)¹⁵. Teachers also reported having to recalibrate their scale when rating

¹⁵This time was computed by the researchers to account for workers accepting multiple HITs at the same time, however, the *WorkTimeInSeconds* reported in the AMT results shows similar trends.

the GPT-2 generated stories, as the stories were significantly worse than the human-written text. Consequently, they suggested that it would be easier to calibrate their scale had the GPT-2 output been presented beside the human-written text, which supports the results from our joint rating task with AMT workers. Finally, the teachers suggested that creating a standardized rubric would greatly facilitate the rating process. This step is even more important as machine-generated text faces different issues than human-written text.

Resolving teacher disagreement: One advantage of using human expert raters is that we can easily have them discuss examples on which they disagree. We arranged a mediation meeting between two of the three teachers to discuss 60 stories on which they showed the highest disagreement (3 attributes \times 10 stories \times 2 types, we excluded *likability* due to its subjective nature). In this meeting, they were first asked to rate the stories again, without being provided their previous rating. In about 20% of cases, one of the teachers disagreed with their own previous rating due to honest lapses of judgment. Another common reason for disagreement was missing world knowledge (see Figure 1, right). One more reason for disagreement, a confusion about how to rate slang in terms of *grammaticality*. While the text was not correct in the view of the official grammar, it was appropriate for the prompt, so one teacher rated it high while the other rated it low. Overall, after discussing examples that they still disagreed on after re-rating, teachers were able to come to a consensus on 80% of the stories; the remaining disagreements persisted due to individual differences in strictness. See Appendix C for details on the mediation meeting.

Replicating the study on Upwork: We recognize that replicating our study is difficult without access to a network of English teachers. As such, we performed the same experiment using three certified teachers recruited on a freelance platform, Upwork.¹⁶ The teachers were paid \$175 for evaluating the same 200 human-written and 200 GPT-2 generated stories using the exact same setup as in subsection 3.1. It took approximately one week to collect the data (including break between rating human-written and GPT-2 generated stories). The results obtained via Upwork were comparable with the results obtained from the English teachers de-

¹⁶<https://www.upwork.com>

scribed in this section, i.e. the Upwork teachers rated human-written stories higher for *coherence*, *relevance*, and *likability* than the GPT-2 generated stories (all p 's < 0.001). Interestingly, their IAA was higher than the English teachers recruited from the authors' personal networks. The details of this experiment are provided in the [Appendix B](#).

5 Related Work

Our work is related to previous studies of human evaluation of text quality as well as collecting judgments using Amazon Mechanical Turk.

Human evaluation of text quality: Most previous studies on human evaluation concentrate on constrained generation domains, such as machine translation ([Guzmán et al., 2015](#); [Graham et al., 2017](#); [Toral et al., 2018](#); [Castilho, 2021](#)) or summarization ([Gillick and Liu, 2010](#); [Iskender et al., 2020](#)). Other studies evaluate very short, often one sentence long, outputs ([Grundkiewicz et al., 2015](#); [Mori et al., 2019](#); [Khashabi et al., 2021](#)).

Even professional translators struggle when evaluating longer machine translated texts ([Castilho, 2021](#)). Creative texts, such as stories, are less constrained than translated texts, but researchers continue to employ crowd workers to evaluate creative texts, often without evaluating reference texts (see [Section 2](#)). Previous studies have asked workers to choose from ([Mori et al., 2019](#)) or distinguish between human-written and machine-generated texts ([Garbacea et al., 2019](#); [Ippolito et al., 2020](#); [Clark et al., 2021](#)).

Data collection using AMT: Many previous works raise concerns about the reliability of data collected on AMT ([Necka et al., 2016](#); [Matherly, 2019](#); [Ahler et al., 2020](#)). Reluctance of requesters to reject HITs leads to positive bias in workers' qualifications ([Matherly, 2019](#)). Furthermore, a large number of responses are provided by small number of productive workers ([Fort et al., 2011](#); [Robinson et al., 2019](#)). Researchers also report an increasing number of workers use VPNs to mask their location ([Bauer et al., 2020](#)) and contribute lower-quality data ([Moss and Litman; Ahler et al., 2020](#)). Hence, simple quality control measures, such as approval rate or the country of residence as suggested in ([Berinsky et al., 2012](#)), may not be sufficient to effectively filter workers who are spamming a task.

6 Recommendations & Conclusion

Our experiments show that evaluating open-ended generated text is an incredibly challenging task even for expert raters. While AMT is a convenient and affordable solution, we observe that high variance between workers, poor calibration, and cognitively-demanding tasks can lead researchers to draw misleading scientific conclusions (e.g., that human-written text is "worse" than GPT-2's). Simple fixes such as adding strict worker qualifications do not address the root of the problem. As such, we recommend future AMT evaluations implement additional quality control mechanisms (some of which require custom task setups on external servers) such as (1) filtering workers by observed time spent per HIT rather than *WorkTimeInSeconds*, (2) specifying a maximum number of items per worker, (3) employing a pre-task language proficiency test, and (4) providing training HITs to allow workers to calibrate their ratings. Furthermore, we show that researchers can improve rating calibration by presenting machine-generated text alongside human reference text. That said, expert raters such as linguists or language teachers should be used whenever possible as they have already been trained to evaluate written text, and it is not much more expensive (it cost us \$144 to rate 200 stories with AMT vs. \$187.50 with English teachers vs. \$262.5 with Upwork).

7 Ethical Considerations

As with all research that makes use of human subjects, we must carefully reflect on our methodology to minimize the risk of harm to those we ask to evaluate open-ended texts. Specifically, texts from social media sites like Reddit may contain racist, sexist, and other forms of vulgar content. Additionally, neural language models like GPT-2, which have been trained on open domain text crawled from the web, have been shown to generate similarly offensive content. As such, we advocate adequately warning any humans who take part in open-ended text evaluation of the potential for such harms (as we did in our research).

Additionally, crowd workers are frequently underpaid for their labor, which harms both the quality of the research, and more importantly, the ability of these crowd workers to earn an adequate living. As such, we report our hourly wage for both crowd workers and experts. We ensure that crowd workers earn at least \$14 per hour by assuming 50–55

seconds per HIT (though on average our crowd workers were paid substantially higher due to the low average time to completion on each HIT). Our experts averaged around \$20 per hour (not counting mediation).

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Qualifications

Approval Rate	90% (4)	95% (3)	97% (1)	99% (1)
Accepted HITs	500 (1)	1000 (5)	5000 (1)	
English	Resident (6)	Native Speaker (4)	Self-reported (1)	
Other	Complete all ratings (1)		Passed quality check (1)	
<hr/>				
Payment	\$0.05 - \$2 per HIT (8)		\$12 - \$20 per hour (2)	
<hr/>				
Number of Items	< 100 items (9)	100 items (14)	> 100 items (20)	not reported (5)
<hr/>				
Number of Raters	< 3 raters (3)	3 raters (16)	5 raters (13)	> 5 raters (3)
<hr/>				
Likert Scale	3-point (4)	4-point (3)	5-point (24)	6-point (1)
<hr/>				
Ranking Task	two texts (19)	more texts (4)		
<hr/>				
Text Length	sentence (28)	paragraph (21)		

Table A1: Results of the survey from Section 2. Numbers in brackets refer to the number of papers/experiments which employed the given measure.

B Collecting Ratings on Upwork

A Questions Used for the Survey

The paper survey described in Section 2 included the following questions:

- type of the task
- length of rated text
- rated attributes
- rating scale
- labels used for ratings
- definitions of each attribute
- instructions provided to raters
- qualifications and quality control measures employed
- number of rated items
- number of rated systems
- number of raters per item
- inclusion of ground truth
- monetary compensation

We also hired three teachers using the freelancing platform Upwork¹. The teachers were paid \$175 to evaluate the same 200 human-written stories and 200 GPT-2 generated stories. They were asked to perform the ratings on the AMT platform in order to use the same interface as workers on AMT. Similarly to the teachers recruited from the authors' personal network, the teachers recruited on Upwork were asked to rate the 200 human-written stories first and then, after a few days break, provide the ratings for the GPT-2 generated stories. Furthermore, Upwork teachers also held TEFL,² TESOL,³ or CELTA¹³ certificates. Table A3 shows mean ratings and agreement for the data collected on Upwork. Similarly to the results described in Section 4 and summarized in Table A5, the average scores for *coherence*, *relevance*, and *likability* are higher for the human-written stories than for the GPT-2 generated stories (see Table A4).

¹<https://www.upwork.com/>

²Teaching English as a Foreign Language.

³Teaching English to Speakers of Other Languages

Authors	Year	Title	Venue
Akoury et al.	2020	STORIUM: A Dataset and Evaluation Platform for Machine-in-the-Loop Story Generation	EMNLP
Alshomary et al.	2020	Target Inference in Argument Conclusion Generation	ACL
Bosselut et al.	2018	Discourse-Aware Neural Rewards for Coherent Text Generation	EMNLP
Brahman and Chaturvedi	2020	Modeling Protagonist Emotions for Emotion-Aware Storytelling	EMNLP
Chakrabarty et al.	2020b	Generating similes effortlessly like a Pro: A Style Transfer Approach for Simile Generation	EMNLP
Chakrabarty et al.	2020a	R3: Reverse, Retrieve, and Rank for Sarcasm Generation with Commonsense Knowledge	ACL
Clark et al.	2018	Neural Text Generation in Stories Using Entity Representations as Context	NAACL
Donahue et al.	2020	Enabling Language Models to Fill in the Blanks	ACL
Fan et al.	2018	Hierarchical Neural Story Generation	ACL
Fang et al.	2020	Video2Commonsense: Generating Commonsense Descriptions to Enrich Video Captioning	EMNLP
Goldfarb-Tarrant et al.	2020	Content Planning for Neural Story Generation with Aristotelian Rescoring	EMNLP
Gorinski and Lapata	2018	What's this Movie about? A Joint Neural Network Architecture for Movie Content Analysis	NAACL
Goyal and Durrett	2020	Neural Syntactic Preordering for Controlled Paraphrase Generation	ACL
He et al.	2019	Pun Generation with Surprise	NAACL
Hegel et al.	2020	Substance over Style: Document-Level Targeted Content Transfer	EMNLP
Holtzman et al.	2018	Learning to Write with Cooperative Discriminators	ACL
Hsu et al.	2019	Visual Story Post-Editing	ACL
Ippolito et al.	2019	Unsupervised Hierarchical Story Infilling	NAACL
Jiang et al.	2020	Neural CRF Model for Sentence Alignment in Text Simplification	ACL
Krishna et al.	2020	Reformulating Unsupervised Style Transfer as Paraphrase Generation	EMNLP
Kriz et al.	2019	Complexity-Weighted Loss and Diverse Reranking for Sentence Simplification	NAACL
Li et al.	2018	Delete, Retrieve, Generate: A Simple Approach to Sentiment and Style Transfer	NAACL
Lin et al.	2020	Learning to Generate Multiple Style Transfer Outputs for an Input Sentence	ACL
Liu et al.	2019	Towards Explainable NLP: A Generative Explanation Framework for Text Classification	ACL
Mallinson et al.	2020	Zero-Shot Crosslingual Sentence Simplification	EMNLP
Martins et al.	2020	Sparse Text Generation	EMNLP
Mir et al.	2019	Evaluating Style Transfer for Text	NAACL
Peng et al.	2018b	Towards Controllable Story Generation	NAACL
Pezeshkpour et al.	2018	Embedding Multimodal Relational Data for Knowledge Base Completion	EMNLP
Qin et al.	2020	Embedding Multimodal Relational Data for Knowledge Base Completion	EMNLP
Qin et al.	2019	Counterfactual Story Reasoning and Generation	EMNLP
Rao and Tetreault	2018	Dear Sir or Madam, May I Introduce the GYAFD Dataset: Corpus, Benchmarks and Metrics for Formality Style Transfer	NAACL
Rashkin et al.	2020	PLOT MACHINES: Outline-Conditioned Generation with Dynamic Plot State Tracking	EMNLP
Shen et al.	2019	Towards Generating Long and Coherent Text with Multi-Level Latent Variable Models	ACL
Sudhakar et al.	2019	"Transforming" Delete, Retrieve, Generate Approach for Controlled Text Style Transfer	EMNLP
Tu et al.	2019	Generating Diverse Story Continuations with Controllable Semantics	EMNLP
Tu et al.	2019	Can Humor Prediction Datasets be used for Humor Generation? Humorous Headline Generation via Style Transfer	ACL
Xu et al.	2020	MEGATRON - CNTRL : Controllable Story Generation with External Knowledge Using Large-Scale Language Models	EMNLP
Yang et al.	2019	An End-to-End Generative Architecture for Paraphrase Generation	EMNLP
Modi and Parde	2019	The Steep Road to Happily Ever After: An Analysis of Current Visual Storytelling Models	NAACL
Yu and Wan	2019	How to Avoid Sentences Spelling Boring? Towards a Neural Approach to Unsupervised Metaphor Generation	NAACL
Yu et al.	2018	A Neural Approach to Pun Generation	ACL
Yu et al.	2020	Routing Enforced Generative Model for Recipe Generation	EMNLP
Zhang and Tetreault	2019	This Email Could Save Your Life: Introducing the Task of Email Subject Line Generation	ACL
Zang et al.	2019	Automated Chess Commentator Powered by Neural Chess Engine	ACL

Table A2: List of Surveyed Papers.

Experiment description	Grammar		Coherence		Relevance		Likability	
	Mean _{STD}	IAA%	Mean _{STD}	IAA%	Mean _{STD}	IAA%	Mean _{STD}	IAA%
Reference	4.28 _{0.78}	0.29 ₂₆	4.55 _{0.66}	0.11 _{30.5}	4.25 _{0.88}	0.49 _{26.4}	4.02 _{1.16}	0.01 _{14.5}
GPT-2	4.25 _{0.82}	0.12 ₁₉	3.99 _{0.98}	0.06 _{12.5}	3.02 _{1.53}	0.25 ₅	3.68 _{1.15}	0.05 _{10.5}

Table A3: Ratings of human-written reference stories and GPT-2 generated stories collected on **Upwork**. Inter-annotator agreement (IAA) between the three raters is measured with Krippendorff’s α well as the percentage of stories for which all three raters exactly agreed on a rating (the latter is subscripted)

	mean (human)	mean (GPT-2)	difference	95% CI lower	95% CI upper	t	df	p-val
grammar	4.28	4.25	0.03	-0.06	0.12	0.72	1194.9	0.47
coherence	4.55	3.99	0.56	0.46	0.65	11.46	1044.3	<0.001
relevance	4.02	3.02	1.00	0.85	1.15	12.82	1103.8	<0.001
likability	4.23	3.83	0.40	0.30	0.53	7.24	1143.4	<0.001

Table A4: Welch’s t -test for ratings collected on **Upwork** (human-written stories vs GPT-2 generated stories). Human-written stories were rated higher on *coherence*, *relevance*, and *likability* than GPT-2 generated stories. These results are similar to the one obtained from English teachers described in Section 4.

C Details on Post-rating Interviews

Two mediation meetings were organized with two of the three teachers (due to availability) over Zoom ⁴. The teachers were asked to reevaluate 60 stories on which they showed disagreement (3 attributes \times 10 stories \times 2 types; *likability* was excluded due to its subjective nature). Each meeting took approximately 2h (including a short break) and was led by one of the authors. The teachers were shown one story at a time and were asked to reevaluate it on the given attribute. In about 20% of the cases, the teachers agreed with each other, suggesting that the previous disagreement was due to honest lapses of judgment. As for the cases where disagreement occurred, each was asked to provide a justification for their ratings. Often hearing the other party’s argument enabled them to see the text from a different perspective and understand the ratings of the other person. This process often resulted in them adjusting their own ratings. Common reasons for disagreement which could be resolved during the mediation meeting included: world knowledge, difference in understanding of the prompt and its relation to the text (e.g., prompt enforcing specific style), difference in the way they treated author’s comments which were sometimes present at the beginning of the story, and rationalizing connections between the sentences.

After each batch, consisting of ratings of both human-written stories and GPT-2 generated stories, each of the three teachers took part in a short one-on-one interview (\sim 10min each). They were asked the following questions:

1. How long did it take you to calibrate your ratings?
2. Explain in more detail how you rated *coherence/grammar/likability/relevance*? What was the process. Did you have to reread the text?
3. How did you calibrate the ratings for *coherence/grammar/likability/relevance*? What constituted a 5? What about a 1?
4. How often did you take breaks?
5. Which attribute was the easiest to calibrate? Which was the most difficult?
6. Any other comments or suggestions?

Additionally, after the second batch of GPT-2 stories, the teachers were also asked: (1) which batch was better written, (2) which batch included more computer generated stories and to what extent, (3) whether they had to recalibrate their ratings, and (4) whether they would prefer to see both batches at the same time.

D Statistical Analysis

⁴<https://zoom.us/>

	mean (human)	mean (GPT-2)	difference	95% CI lower	95% CI upper	t	df	p-val
grammar	4.50	4.55	0.05	-0.14	0.03	-1.27	1111.7	0.21
coherence	4.38	3.73	0.65	0.53	0.77	10.63	1119.6	<0.001
relevance	3.82	2.54	1.28	1.12	1.44	15.45	1190.7	<0.001
likability	3.69	2.96	0.73	0.57	0.89	9.16	1182	<0.001

Table A5: Welch’s *t*-test for ratings collected in the experiment described in Section 4 (teachers’ ratings). Human-written stories were rated higher for *coherence*, *relevance*, and *likability* than GPT-2 generated stories.

Please Rate the Story Fragment

The goal of this task is to rate story fragments on four criteria.

NOTE: Please take the time to **fully read** and **understand** the story fragment. **We will reject** submissions from workers that are clearly spamming the task.

Story Fragment

The night before came as a shock for Oren, he was always a conscientious child. It was a necessary skill of a new master, an inherent capability to make the world a better place. But no, today, the day he brought his sister to his cooking school was the first time Oren had been shocked out of a small calm. He looked over at his sister in the small room, who was idly flipping through the magazine he had brought with him, and then back to the breakfast. It took all his willpower to stay calm, he could tell from the way the noodles he was looking at were slathered in gherkin and he felt the freshness of the rice. He shook his head in disbelief, his stomach began to churn and he was too exhausted to react, he was just preparing to go to bed.

- How **grammatically correct** is the text of the story fragment? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)
- How well do the **sentences** in the story fragment **fit together**? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)
- How **enjoyable** do you find the story fragment? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)
- Now read the **PROMPT** based on which the story fragment was written.
PROMPT: After brushing your teeth in the morning you go downstairs to fry an egg, but when you try the frying pan buzzes at you and text appears reading, "level 18 cooking required to use object".
How **relevant** is the story fragment to the prompt? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)

Figure A1: AMT interface for evaluation of one story.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	η_p^2
Group	3	13.63	4.54	4.90	0.002	0.01
Residuals	2396	2223.51	0.93			

Table A6: One-way ANOVA investigating the effect of group (Day 1, Day 2, Day 3, and workers from non-English-speaking countries) on the ratings of *grammar* of the reference texts. Partial eta squared (η_p^2) is provided for the effect size ($\eta_p^2 = 0.01$ indicates small effect size; $\eta_p^2 = 0.06$ indicates medium effect size; $\eta_p^2 = 0.14$ indicates large effect size (Cohen, 1988)).

	Day 1	Day 2	Day 3
Day 2	0.08		
Day 3	1.00	0.20	
NNS	0.01	1.00	0.03

Table A7: Pairwise post-hoc test with Bonferroni adjustment for the ratings of *grammar* between Day 1, Day 2, Day 3, and non-English speaking countries (NNS). The numbers provided in the table are *p*-values for the given pairwise comparison. Grammar ratings provided by the workers from non-English speaking countries are significantly different from ratings provided by the workers from English-speaking countries on Day 1 and Day 3⁵

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	η_p^2
Group	3	161.28	53.76	51.35	<0.001	0.06
Residuals	2396	2508.21	1.05			

Table A8: One-way ANOVA investigating the effect of group (Day 1, Day 2, Day 3, and workers from non-English-speaking countries) on the ratings of *coherence* of the reference texts. Partial eta squared (η_p^2) is provided for the effect size ($\eta_p^2 = 0.01$ indicates small effect size; $\eta_p^2 = 0.06$ indicates medium effect size; $\eta_p^2 = 0.14$ indicates large effect size (Cohen, 1988)).

Please Rate the Story Fragment 1

The goal of this task is to rate story fragments on four criteria.

NOTE: Please take the time to **fully read and understand** the story fragment. **We will reject** submissions from workers that are clearly spamming the task.

Story Fragment 1

"Man, Clark? You've never been the greatest detective, but do I even need to tell you this? The invaders might be all talk and no walk, but the Jackal Boy has the sense of an eagle to stick to his arse." Clark was about to say something, but he didn't want to risk it. He didn't like it when people were talking about him in such a nice light. He wasn't about to go walking into someone's bar. He certainly wasn't about to try to convince himself that the local kids were going crazy. "Psh, psh, this doesn't feel right. I don't want to stick my nose where you don't want to smell it, Gordon. You shouldn't say that about yourself. All of you." He stared at Gordon, dumbfounded. This wasn't Gordon's first rodeo, this was something new.

- How **grammatically correct** is the text of the **story fragment 1**? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)
- How well do the **sentences** in the **story fragment 1** **fit together**? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)
- How **enjoyable** do you find the **story fragment 1**? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)
- Now read the **PROMPT** based on which the **story fragment 1** was written.
PROMPT: With the earth currently under attack by aliens, Clark Kent searches for a place to change into his super suit. He decides to use the blue police public call box standing curiously in the middle of the street.
How **relevant** is the **story fragment 1** to the **prompt**? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)

Please Rate the Story Fragment 2

The goal of this task is to rate story fragments on four criteria.

NOTE: Please take the time to **fully read and understand** the story fragment. **We will reject** submissions from workers that are clearly spamming the task.

Story Fragment 2

He burst through the door like he owned the place. Silly, really, even I only "sorta" own her. I glanced across the console, and Clara caught my eye. "Oi," called Clara. I scowled at him (scowling has actually become rather easy lately) as he turned around. He was still wearing those stupid round spectacles. It was early in his career, then. He scanned the room quickly, processing his surroundings. He didn't seem surprised by the interior dimensions, at least. He loosened his tie, dropping the coat he'd been wearing. "What is this? Some sort of trap?" He looked tense, ready to strike. "Oh, that's lovely, isn't it." I said with a sarcastic chuckle, smirking at Clara. "You burst in here and then "you're" the one who's angry. How do you think we feel, hm?" Whatever he'd been expecting, it wasn't that.

- How **grammatically correct** is the text of the **story fragment 2**? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)
- How well do the **sentences** in the **story fragment 2** **fit together**? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)
- How **enjoyable** do you find the **story fragment 2**? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)
- Now read the **PROMPT** based on which the **story fragment 2** was written.
PROMPT: With the earth currently under attack by aliens, Clark Kent searches for a place to change into his super suit. He decides to use the blue police public call box standing curiously in the middle of the street.
How **relevant** is the **story fragment 2** to the **prompt**? (on a scale of 1-5, with 1 being the lowest)
(lowest) 1 2 3 4 5 (highest)

Figure A2: AMT interface for evaluation of both types of stories (GPT-2 and human reference).

	Day 1	Day 2	Day 3
Day 2	1.00		
Day 3	<0.001	<0.001	
NNS	<0.001	<0.001	0.02

Table A9: Pairwise post hoc test with Bonferroni adjustment for the ratings of *coherence* between Day 1, Day 2, Day 3, and non-English speaking countries (NNS). The numbers provided in the table are p -values for the given pairwise comparison. Ratings of *coherence* provided by raters from non-English speaking countries are significantly different from ratings of workers from English-speaking countries. Furthermore, there are some difference between Day 1, Day 2, and Day 3.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	η_p^2
Group	3	89.99	30.00	19.92	<0.001	0.02
Residuals	2396	3607.85	1.51			

Table A10: One-way ANOVA investigating the effect of group (Day 1, Day 2, Day 3, and workers from non-English-speaking countries) on the ratings of *relevance* of the reference texts. Partial eta squared (η_p^2) is provided for the effect size ($\eta_p^2 = 0.01$ indicates small effect size; $\eta_p^2 = 0.06$ indicates medium effect size; $\eta_p^2 = 0.14$ indicates large effect size (Cohen, 1988)).

	Day 1	Day 2	Day 3
Day 2	0.01		
Day 3	1.00	0.14	
NNS	<0.001	<0.001	<0.001

Table A11: Pairwise post hoc test with Bonferroni adjustment for the ratings of *relevance* between Day 1, Day 2, Day 3, and non-English speaking countries (NNS). The numbers provided in the table are p -values for the given pairwise comparison. Ratings obtained from workers from non-English speaking countries differ significantly from ratings obtained from workers from English-speaking countries on Day 1, Day 2, and Day 3. Furthermore, there is a significant difference between ratings collected on Day 1 and Day 2.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	η_p^2
Group	3	62.70	20.90	15.89	<0.001	0.02
Residuals	2396	3151.22	1.32			

Table A12: One-way ANOVA investigating the effect of group (Day 1, Day 2, Day 3, and workers from non-English-speaking countries) on the ratings of *likability* of the reference texts. Partial eta squared (η_p^2) is provided for the effect size ($\eta_p^2 = 0.01$ indicates small effect size; $\eta_p^2 = 0.06$ indicates medium effect size; $\eta_p^2 = 0.14$ indicates large effect size (Cohen, 1988)).

	Day 1	Day 2	Day 3
Day 2	<0.001		
Day 3	1.00	<0.001	
NNS	1.00	<0.001	0.75

Table A13: Pairwise post hoc test with Bonferroni adjustment for the ratings of *likability* between Day 1, Day 2, Day 3, and non-English speaking countries (NNS). The numbers provided in the table are p -values for the given pairwise comparison. Ratings provided by workers from non-English speaking countries differ significantly from ratings obtained from workers from English-speaking countries on Day 2. Furthermore, there are significant differences between ratings obtained on Day 1 and Day 2, as well as between ratings obtained on Day 2 and Day 3.

	mean (human)	mean (GPT-2)	difference	95% CI lower	95% CI upper	t	df	p -val
grammar	4.00	3.94	0.06	-0.05	0.16	1.06	1197.9	0.29
coherence	4.11	3.82	0.29	0.18	0.42	4.97	1169.1	<0.001
relevance	3.71	3.44	0.27	0.12	0.43	3.54	1184.7	<0.001
likability	3.37	3.42	0.05	-0.18	0.09	-0.64	1194.5	0.52

Table A14: Welch's t -test on ratings collected on AMT for human-written stories (Day 1) and GPT-2 generated stories. Human-written stories are being rated higher for *coherence* and more *relevance* than GPT-2 generated stories ($p < 0.05$).

	mean (human)	mean (GPT-2)	difference	95% CI lower	95% CI upper	t	df	p -val
grammar	3.86	3.94	0.08	-0.19	0.03	-1.50	1197.9	0.14
coherence	3.92	3.82	0.10	-0.02	0.23	1.72	1176.5	0.09
relevance	3.71	3.44	0.27	0.13	0.41	3.69	1123.5	<0.001
likability	3.73	3.42	0.31	0.19	0.44	4.89	1128.9	<0.001

Table A15: Welch's t -test on ratings collected on AMT for human-written stories (Day 2) and GPT-2 generated stories. Human-written stories were rated higher for *relevance* and *likability* than GPT-2 generated stories ($p < 0.05$).

	mean (human)	mean (GPT-2)	difference	95% CI lower	95% CI upper	t	df	p -val
grammar	3.98	3.94	0.04	-0.07	0.15	0.70	1196.4	0.48
coherence	4.05	3.82	0.23	0.12	0.36	3.98	1163.5	<0.001
relevance	3.46	3.44	0.02	-0.13	0.17	0.27	1188.9	0.80
likability	3.42	3.42	0.00	-0.14	0.14	0.00	1192.5	1

Table A16: Welch's t -test for ratings collected on AMT for human-written stories (Day 3) and GPT-2 generated stories. Human-written stories were rated higher for *coherence* than GPT-2 generated stories ($p < 0.05$).

	mean (human)	mean (GPT-2)	difference	95% CI lower	95% CI upper	t	df	p-val
grammar	3.82	3.94	0.12	-0.23	-0.01	-2.11	1183.1	0.04
coherence	3.45	3.82	0.37	-0.49	-0.23	-5.42	1194.2	<0.001
relevance	3.25	3.44	0.19	-0.35	-0.04	-2.50	1185	0.01
likability	3.32	3.42	0.10	-0.24	0.04	-1.41	1197.9	0.16

Table A17: Welch's *t*-test for ratings collected on AMT for human-written stories (non-English speaking countries) and GPT-2 generated stories. GPT-2 generated stories were rated *higher* for *grammar*, *coherence*, and *relevance* than human-written stories ($p < 0.05$)

	mean (human)	mean (GPT-2)	difference	95% CI lower	95% CI upper	t	df	p-val
grammar	3.83	3.82	0.01	-0.09	0.12	0.28	1188.1	0.78
coherence	3.83	3.39	0.44	0.32	0.57	6.92	1198	<0.001
relevance	3.49	2.70	0.79	0.65	0.93	10.85	1198	<0.001
likability	3.48	2.99	0.49	0.37	0.62	7.72	1195.2	<0.001

Table A18: Welch's *t*-test for ratings collected on AMT for human-written stories and GPT-2 generated stories (both stories shown in one HIT). GPT-2 generated stories were rated lower for *coherence*, *relevance*, and *likability* than human-written stories ($p < 0.05$) which is in line with the ratings provided by English teachers.