A Token-level Reference-free Hallucination Detection Benchmark for Free-form Text Generation

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Abstract

Large pretrained generative models like GPT-3 often suffer from hallucinating non-existent or incorrect content, which undermines their potential merits in real applications. Existing work usually attempts to detect these hallucinations based on a corresponding oracle reference at a sentence or document level. However ground-truth references may not be readily available for many free-form text generation applications, and sentence- or document-level detection may fail to provide the fine-grained signals that would prevent fallacious content in real time. As a first step to addressing these issues, we propose a novel token-level, reference-free hallucination detection task and an associated annotated dataset named HADeS (HAllucination DEtection dataSet). To create this dataset, we first perturb a large number of text segments extracted from English language Wikipedia, and then verify these with crowd-sourced annotations. To mitigate label imbalance during annotation, we utilize an iterative model-in-loop strategy. We conduct comprehensive data analyses and create multiple baseline models.

1 Introduction

Automatic text generation using neural natural language generation (NLG) systems is increasingly fluent and thus seemingly plausible in many real-world applications. Large-scale pretrained models like GPT-3 (Brown et al., 2020) are proven to be powerful in understanding and performing free form text generation tasks at human-quality level with a few in-context examples, which dramatically reduces the manual labor needed in many text-based applications and services. Despite their great success, however, neural NLG systems using very large pre-trained models struggle to generate factually accurate and trustworthy text (Devlin et al., 2019; Radford et al., 2019), and exhibit a propensity to hallucinate non-existent or incorrect content that is unacceptable in most user-oriented applications. This poses a major challenge for deploying production NLG systems with realtime generation, where post-examination is impossible.

Existing work has sought to detect hallucination and quantitatively measure generation consistency against a provided reference. Such reference-based hallucination detection has been proposed for abstractive summarization (Maynez et al., 2020), machine translation (Wang and Sennrich, 2020), data-to-text generation (Rebuffel et al., 2021), and image caption generation (Rohrbach et al., 2018). For many free-form text generation tasks, however, references are not readily available. For example, in a production NLG system such as a social chatbot using real-time response generation or a document auto-completion system, the generation model often cannot pair its outputs with sufficient reference information, rendering reference-based methods less applicable: i) It may be difficult to even know where to obtain the reference, as obtaining it may be as hard as generating consistent information in the first place; ii) Generation may require multiple factual references with an understanding of their relationships; iii) Generation may be at a real-time online setting that demands leveraging only existing context to create new content.

One common setup for qualitatively measuring the level of hallucination is that the detection is performed at sentence- or document-level (Dhingra et al., 2019; Scialom et al., 2019). Related tasks such as fake news detection (Zellers et al., 2019) or fact checking (Thorne and Vlachos, 2018) also adopt this strategy. From a pragmatic point of view, however, sentence- or document-level detection may not always provide high-resolution signals suf-
efficient to pinpoint the hallucinated text, or can only judge whether a generated sentence or a document as a whole is a hallucinated artifact. Consequently, these high-level strategies may be insufficient to avoid hallucinating information. As an alternative, at decoding time of an NLG system, we suggest that if the locus of hallucination can be identified at the token level, it may be possible to guide beam search or suppress the probability of certain tokens at real-time.

To address the above issues, we propose a reference-free, token-level hallucination detection task and introduce an annotated training and benchmark testing dataset that we call HADES (HAllucination DEtection dataS). The reference-free property of this task yields greater flexibility in a broad range of generation applications. We expect the token-level property of this task to foster the development of models that can detect fine-grained signals of potential hallucination. In conjunction with consulting context to identify self-contradictory statements and access to commonsense and world knowledge, such fine-grained signals, when detected, should further mitigate real-time hallucination.

Our contributions are as follows:

- We propose a reference-free, token-level hallucination detection task for free-form text generation.
- We support this task with a dataset that we call HADES, with ~11k instances extracted from English-language Wikipedia and developed using an iterative data collection strategy to address data imbalance issues. We present comprehensive analyses of the statistical features of this dataset to shed light on what is commonly recognized as hallucination in crowd-sourced judgments and its salient characteristics in free-form text generation.
- We create multiple baselines, including feature-based models and pretrained models as a first step towards addressing the proposed task.

2 Task Overview

We formulate our hallucination detection task as a binary classification task. As shown in Fig 1, our goal is to assign either a “hallucination” or a “not hallucination” label to the highlighted word spans. In the following sections, we abbreviate “hallucination” and “not hallucination” classes as “H” and “N”.

To simulate real-world NLG applications, we propose two sub-tasks with “offline” and “online” settings. In the offline setting, it is assumed that generation is complete, so the model is able to perceive the bidirectional context. This could be used in the post-generation examination of NLG systems. For online detection, the model can only access the unidirectional preceding context, which simulates on-the-fly generation. Online detection is important in practice as it enables NLG systems to proactively forestall potential hallucinations.

3 Dataset Creation

To collect the HADES dataset, we first perturb “raw text” web data into “perturbed text” (Fig 2A) (Sec 3.2). We then ask human annotators to assess whether the perturbed text spans are hallucinations given the original text (Fig 2B) (Sec 3.3).

3.1 Raw Data Collection

Our raw data are sampled from English WIKI-40B (Guo et al., 2020) dataset. WIKI-40B-EN is a cleaned collection of English Wikipedia articles. We randomly sample from the first paragraphs of...
these articles and filter out short text of fewer than 5 sentences. We use Wikipedia as our text source since it is stylistically formal and of high quality, and covers diverse topics and domains.

3.2 Contextual Perturbation
To acquire machine generated text in the free-form, we perturb the raw text\(^2\) using BERT. In applying this contextual perturbation, we maintained two principles: i) the fluency and syntactic correctness of the perturbed text should be preserved; ii) the perturbed text should be lexically diverse.

We leave the first two sentences in the raw text unchanged to serve as the preceding context, so as to avoid the “early token curse” (Press et al., 2020) where tokens are evaluated at the beginning with limited context. The text perturbation process is split into three pipelined operations, namely \texttt{MASK}, \texttt{REPLACE} and \texttt{RANK}.

- In the \texttt{MASK} operation, we mask the tokenized words to be replaced with the special token “[MASK]” in the BERT vocabulary. Starting from the third sentence, we randomly mask word spans by a pre-defined mask ratio \(\rho\). By default, we only mask one word in each perturbation, except for named entities identified by \texttt{Spacy}\(^3\). We view the entity boundaries as minimal masking units to avoid collocation errors (e.g., “San Diego” should be masked as a whole). To reduce trivial instances, we do not mask stop words or punctuation identified by NLTK (Bird, 2006).

- In the \texttt{REPLACE} operation, we leverage a pretrained BERT-base model to predict the masked span. The mask-then-predict training framework of the BERT model contextualizes the replacement with both preceding and subsequent text. For better fluency, we replace the masked tokens from left to right, e.g., a 3-token \texttt{REPLACE} operation will be “[MASK] [MASK] [MASK]” \(\rightarrow\) “[A] [MASK] [MASK]” \(\rightarrow\) “[A] [B] [MASK]” \(\rightarrow\) “[A] [B] [C]”. When performing the replacement, we remove the original token from the predicted distribution over the vocabulary at each position of the text span, to avoid generating the same text after perturbation.

We compared several decoding strategies in token substitution, including greedy, top-k (k=5/10/50) and top-p (p=0.95/0.9/0.8) (Holtzman et al., 2020) sampling methods. For fair comparison, we sample 30 perturbed text for each sampling method and count the number of incoherent perturbations. We choose top-k (k=10) sampling as it achieves a good trade-off between diversity (via number of distinct tokens) and coherence (via number of incoherent perturbations).

- For each perturbed text, we substitute multiple word spans. Although being locally coherent, the perturbed text may still exhibit some global incoherence and syntactic issues, especially when the original text is long. We thus post-process the perturbed text with a \texttt{RANK} operation as an additional screening step. For each raw text, we generate 20 perturbed candidates and rank them according to language model perplexity using a GPT-2 (117M) model. We only keep the candidate with lowest perplexity to ensure the fluency and syntactic correctness.

3.3 Data Annotation
We ended up with \(\sim\)1M perturbed text segments in the pool after contextual perturbation, not all of which contain hallucination, as the BERT model can generate factual information given that it is pretrained on a rich open web corpus. Thus, we sought to further annotate the automatically perturbed texts via crowd-sourcing. Human annotation is prohibitively expensive at this scale, so instead of annotating all 1M perturbed texts, we annotated a subset that is more useful and would lead to a more balanced distribution, using an iterative model-in-the-loop annotation approach that is conceptually related to active learning (Cohn et al., 1996; Jia and Liang, 2017; Zellers et al., 2018; Nie et al., 2020).

Human annotation settings To perform the annotations, we hired judges using Microsoft’s internal crowd-sourcing platform. The judges were limited to the North American English speakers and were screened via a simple 10-question qualification test. They were paid more than prevailing minimum wage in Washington State. Protocols were implemented to block spammers in real time.
For each annotation, both original text and perturbed text were shown to the judges, with perturbed text span highlighted. The annotators were asked to determine whether the perturbed text spans are $\mathcal{H}$ (hallucination) or $\mathcal{N}$ (not hallucination) with the original text in terms of factualness and semantic coherence given the context.\(^5\)

Each pair was judged by 4 annotators, and up to 6 if consensus was not reached. We retained only those annotations for which consensus was reached.

**Iterative model-in-the-loop annotation** Annotating all perturbed text segments is expensive and time-consuming. Thus, we resort to annotating a subset. We applied two principles for selecting the data to be annotated: \(i\) the data should be balanced. We found that with randomly sampled instances, the annotated label distribution is heavily skewed toward the “hallucination” class. Presumably most contextualized perturbations result in factual inconsistency to certain extent. However, we aim to have the number of instances in both classes on par with each other, so that the ROC (receiver operating characteristic) curve of tested models can be better characterized. \(ii\) the data for annotation should be useful. Many perturbations are trivial to predict, \(e.g.\) replacements that change a specific date to a non-date-related phrase must be a hallucination. These obvious instances contribute little to model training and method benchmarking, but cost as much annotation effort as more valuable instances.

The challenge is that we cannot know \textit{a priori} the annotation labels and ease of labelling, hence selecting useful labels and forming a balanced label distribution for annotation is not straightforward. To address this challenge, we adopt an iterative \textit{Model-in-the-loop} annotation strategy. Specifically, we split the annotations into several rounds. For each round \(^6\), we first retrain a hallucination detection model (initiated with BERT) based on the annotated instances in the previous rounds. This model is used for selecting the next batch of data to be annotated from the remaining unlabeled data.

To filter out trivial instances and focus on the more useful cases, we use a heuristic rule for the automatic screening by abandoning instances where the detection model assigns low or high probability to “hallucination” class (the threshold varies in different rounds to yield reasonable number of candidates to be annotated). To eliminate cases where the perturbed text paraphrases the original text, we also measured the cosine similarity between the representation (contextualized representation for “[CLS]”) of replaced text and corresponding original content using a RoBERTa model (without fine-tuning), and then filtered out cases with a similarity score greater than 0.9. We also remove a large portion of obvious hallucination instances where the target text span is recognized as a DATE or NAME by NER, and replaced by a different DATE\(^7\) or NAME.

In the initial rounds of annotation, we observed extreme label imbalance (around 90% are $\mathcal{H}$ class) between $\mathcal{H}$ (hallucination) and $\mathcal{N}$ (not hallucination) cases. To rebalance the label distribution so that each class received a decent amount of annotation, we performed additional subsampling based on the label predicted by the aforementioned detection model. We assume the human annotation for $\mathcal{H}$ and $\mathcal{N}$ cases is the oracle, indicating actual $\mathcal{H}/\mathcal{N}$. Since the actual “hallucinated” is dominant, we seek to subsample from instances that are predicted as $\mathcal{H}$ by the detection model to make the distribution of actual $\mathcal{H}/\mathcal{N}$ even. To do this, we estimate the true positive rate\(^8\) (TPR, $\alpha$), true negative rate (TNR, $\beta$) and true precision ($\gamma$) of the detection model based on the annotation from last round. The hope is that after subsampling, the actual $\mathcal{H}$ (TP + FN) is roughly equal to actual $\mathcal{N}$ (FP + TN). The estimated subsampling ratio $R$ for the predicted $\mathcal{H}$ (TP + FP) is given by (details are provided in the Appendix):

$$R = \frac{-2\alpha\beta\gamma + \alpha\beta + \beta\gamma + \alpha\gamma - \gamma}{(2\gamma - 1)\alpha(1 - \beta)}$$ (1)

### 3.4 Data Analysis

Below we provide data statistics and characterize the composition and properties of the collected data.

**Data statistics** In total, after accumulating annotations for several rounds, we obtain 12,719 instances with 71,226 HITS from judges. We con-

\(^5\)The template for the human annotation interface is provided in the Appendix.

\(^6\)Except the first round, where we simply randomly sample from all the perturbed text segments.

\(^7\)We only remove cases where the replaced date is \textit{definitely} different from the original one (\(e.g.\), from “Monday” to “Tuesday”). We do not remove ambiguous cases such as from “today” to “Tuesday”.

\(^8\)Defining $\mathcal{H}$ as the positive class.
Machine Generated Text in HADES (Hallucination → Factuality)  

| He became deputy major-general to the forces, with the acting rank of brigadier general. (brigadier → major) | Domain-specific Knowledge |
| Retirement compensation arrangements (RCAS) are ... no tax is paid by the owner / employee until benefits are received at death. (death → retirement) | Commonsense knowledge |
| This meeting discussed the drug and alcohol problems for many in their community. (many → teenager) | Incoherence or improper collocation |
| ... is a designer / craftsman ... he has also produced one-of-a-kind tables, chairs, and other furniture ... the New York Times described him as one of 2019’s leading businessmen. (businessmen → chair makers) | Unrelated to the central topic |
| Alfonzo Florez Ortiz ... was a Colombian road racing cyclist from 1985 to 1987 ... he was born in April, 1992 in Medellin. (born → died) | Conflict with preceding context |
| He also aided prominent documentary writer Joseph Margulies on his book, Guantanamo and the Abuse of Presidential Power. (documentary writer → civil rights attorney) | Conflict with succeeding context |

Table 1: Analysis for statistical and model-based features of HADES.  

| Label | Word Prob* | Entropy | TF-IDF | PPMI |
|-------|------------|---------|--------|------|
| $\mathcal{H}$ | 5.85 | 2.585 | $0.021_{0.19}$ | $0.198_{0.134}$ |
| $\mathcal{N}$ | 1.307 | 1.781 | 0.019 | 0.216 |

(A) Mean stats for Hallucination ($\mathcal{H}$) and not Hallucination ($\mathcal{N}$) labels (* indicates $\times 10^{-3}$).  

(B) Feature correlation heatmap between hallucination label and word probability, entropy, TF-IDF and PPMI.

Table 1: Analysis for statistical and model-based features of HADES.  

We compute the correlation between a selected group of statistical/model-based features and hallucination labels. As shown in Table 1, we obtain the average word probability and average word entropy of a given text span with a BERT base model (without fine-tuning), as well as term frequency–inverse document frequency (TF-IDF), positive pointwise mutual information (PPMI) features of the given word span. By comparing the features of the two labels ($\mathcal{H}/\mathcal{N}$) (Table 1A), we observe that in our dataset, hallucinations typically associate with higher entropy. A counter-intuitive observation is that the hallucinations tend to have lower word probability.

**Parsing features**  
In Fig 4 we show the ratio of “hallucination” ($\mathcal{H}$)/ “not hallucination” ($\mathcal{N}$) cases for different Part-of-Speech (POS) and Name Entity Recognition (NER) tags, identified by Spacy. From a POS perspective, around two-thirds of verbs and verbal phrases in the dataset are identified as “not hallucination”, while in other types of words/phrases, “hallucination” cases are in the majority, e.g., most adverbs (ADV), adjectives (ADJ) and acronyms of proper nouns (PROPN) are labeled as “hallucination”. Presumably many verbs or verbal phrases are lower in word concreteness (Nelson and Schreiber, 1992) than other word types (e.g. “make” and “create” can be used interchangeably in many circumstances), and thus, as we observe in our dataset, are less prone to be perturbed into hallucinations. For NER tags, about 90% of word spans are not recognized as name entities. However, of the 10% of remaining instances, over 90% are “hallucination” cases.

**Statistical and model-based features**  
To analyze the characteristics of hallucinations in HADES, we conduct 14 rounds of annotation, increasing the annotation scale with each round (ranging from ~200 instances/round to ~4000 instances/round). Out of 12,719 annotated instances, 10,954 instances reached consensus among judges and are included in the HADES dataset. We split the dataset into train, validation and test sets with sizes of 8754, 1000, 1200 respectively. In the final dataset, “hallucination” cases slightly outnumber “not hallucination” cases, with a ratio of 54.5%/45.5%. We summarize some typical hallucination types seen in the HADES dataset in Fig 3.
higher average probability than factually consistent content. We presume the underlying reason might be that the word distribution generated by machine may diverge from the word distribution of real human-written text (Holtzman et al., 2020; See et al., 2019) owing to self-reinforcing the current generation based on previous generation. Consequently, many overconfident generation outputs are likely to fall into hallucination. We observe no strong correlation between hallucination labels and TF-IDF or PPMI as demonstrated in Table 1B.

4 Baseline Models

As an initial step towards tackling the proposed hallucination detection task and benchmarking methods, we create several baseline detection models.

**Feature-based models**  As elaborated in Sec 3.4, the statistical/model-based features like average word probability, average entropy, TF-IDF, PPMI, as well as parsing features like POS and NER tags can be vague indicators of hallucinations. The former two are context-aware and the latter four are not. We incorporate them as features to build classifiers including logistic regression (LR) and support vector machine (SVM) using scikit-learn (Pedregosa et al., 2011). The maximum number of iteration is set as 100, with an early-stop strategy which stops training if the loss does not drop within 5 iterations.

**Transformer-based models**  We also build baseline detection models based on pretrained transformer models including BERT, GPT-2, XLNet (Yang et al., 2019) and RoBERTa (Liu et al., 2020). These transformer-based models represent the state-of-the-art, and can potentially better leverage context or embedded world knowledge to detect self-contradictory or anti-commonsense content. Specifically, for an input text segment, we fine-tune a pretrained model $M$ to predict binary hallucination labels $y$ for each given text span. During inference time, from the last layer hidden states $H \in \mathbb{R}^{l \times h}$ ($h, l$ are hidden size and sequence length, respectively) of $M$, suppose the target text span starts at position $s$ and ends at position $t$, we first obtain the representation $w \in \mathbb{R}^{h}$ for the target span with max pooling (i.e., $w = \max_{pool}(H_{st})$). We then map $w$ to a binary hallucination label $y \in \{0, 1\}$ with a MLP network using tanh as activation. During training time, we fine-tune the model using cross entropy objective between the predicted labels and the actual labels.

5 Experimental Setup

**Baseline configurations**  For the transformer-based baselines, we experiment with a variety of pretrained models via Hugging Face Transformers (Wolf et al., 2020), including BERT-large (335M), GPT2-medium (345M), XLNet-large (340M), RoBERTa-large (355M). We use Adam optimizer (Kingma and Ba, 2014) with different learning rates, i.e. 5e-3 for GPT2 and BERT and 1e-3 for other models.

We explored multiple model architectures and setups to determine the optimal configuration using BERT-large model. These include $i$) span representation with mean/max pooling; $ii$) number of layers of the MLP network; $iii$) hidden dimension of the MLP; $iv$) whether or not to freeze the parameters of $M$ up to the last layer, and choose the best configuration according to model performance on the validation set. The best configuration uses max-pooling, employs 2 layers of MLP with hidden dimension of $h/2$, and freezes the model parameters up to the last layer of $M$ and just fine-tunes the binary MLP classifier. We apply the same network...
Table 2: Benchmark for the offline setting on HADES, where detecting models have access to the bidirectional context. All reported numbers are percentages (%). ↓/↑ indicates lower/higher is better.

| Model   | Acc  | G-Mean (↑) | BSS (↓) | AUC  | Not Hallucination P | R | F1  | Hallucination P | R | F1  |
|---------|------|------------|---------|------|---------------------|---|-----|-----------------|---|-----|-----------------|---|-----|
| LR      | 62.25| 60.77      | -       | -    | 62.35               | 72.08| 66.86 | 62.10           | 51.24| 60.33          |
| SVM     | 63.67| 61.50      | -       | -    | 62.89               | 76.18| 68.90 | 65.05           | 49.65| 56.31          |
| BERT    | 71.92| 71.95      | 19.06   | 78.63| 74.46               | 71.29| 72.84 | 69.31           | 72.61| 70.92          |
| RoBERTa | 72.83| 70.94      | **18.78**| 78.72| 74.06               | 74.76| 74.41 | 71.43           | 70.67| **71.05**      |
| XLNet   | 72.33| 71.39      | 18.79   | 78.93| 71.15               | **80.13**| **75.37**| 74.07           | 63.60| 68.44          |

Table 3: Benchmark for the online setting on HADES, where detection models only have the access to left context. All reported numbers in percentages (%). ↓/↑ indicates lower/higher is better.

| Model   | Acc  | G-Mean (↑) | BSS (↓) | AUC  | Not Hallucination P | R | F1  | Hallucination P | R | F1  |
|---------|------|------------|---------|------|---------------------|---|-----|-----------------|---|-----|-----------------|---|-----|
| GPT-2   | **71.58**| 70.98      | 19.13   | 77.71| **71.32**           | 77.29| **74.19**| **71.93**           | 65.19| **68.40**      |
| BERT    | 71.00| 70.43      | **18.66**| **78.83**| 70.91           | 76.50| 73.60 | 71.12           | 64.84| 67.84          |
| RoBERTa | 70.67| 70.14      | 19.77   | 77.07| 70.74               | 75.87| 73.22 | 70.58           | 64.84| 67.59          |
| XLNet   | 70.08| 69.17      | 19.76   | 76.59| 69.39               | **77.60**| 73.27 | 71.08           | 61.66| 66.04          |

Figure 5: The performance of BERT-large based detecting model with different context lengths.

Configuration to all other pretrained models as empirically we see marginal performance gain after enumerating different configurations for individual pretrained models other than BERT.

As discussed in Sec.2, HADES can serve as benchmark for hallucination detection in both offline (model can see bidirectional context) and online (only preceding context can be leveraged) settings. Note that we apply the feature-based baselines only in the offline setting in Table 2, because a good estimation of those features typically requires bidirectional context. The transformer with causal attention (GPT-2) can only be applied in the online setting.

Evaluation metrics We evaluate the baselines on HADES with standard classification metrics including accuracy, precision, recall, F1 and AUC (Area Under Curve) with respect to ROC. We also utilize the G-Mean metric which measures geographic mean of sensitivity and specificity (Espíndola and Ebecken, 2005) and they were reported useful especially for the imbalanced label distribution scenarios. We also employ the Brier Skill Score (BSS) metric (Center, 2005), which calculates the mean squared error between the reference distribution and the hypothesis probabilities, to measure the discrepancy between our prediction distribution and the actual label distribution.

6 Results

Baseline performance Table 3 Table 2 show the performance of the baseline models in both online and offline settings respectively. In both settings, the predictions for “not hallucination” cases have higher F1 scores than “hallucination” cases. All models perform better in the offline setting com-
pared with the online setting, indicating that the succeeding context of the target words helps identify hallucinations. The transformer-based baselines are generally on par with each other. Under the offline setting, the pretrained models outperform feature-based models by a large margin; this indicates that the powerful contextualized feature extractor is important for successfully identifying hallucinations at fine granularity. Under the online setting, we observe that, for most of the metrics, GPT-2 yields the best performance of all baselines. Presumably, the causal language model pretraining method makes GPT-2 perform better in the auto-aggressive (online) detection setting.

**Context matters in HADES** To investigate extent to which contextual information helps the hallucination detection in HADES, we run BERT-large detection model with different context lengths and characterize its performance in both online and offline settings in Fig 5. Starting from the target words, we set a fixed size (5/10/20/40/80/160) context window and truncate all text beyond this window. As we enlarge the context window, model performance grows rapidly when context length is smaller than 80, and then gradually converges. This observation highlights the importance of context in hallucination detection. Interestingly, we observe that the model obtains higher performance in the offline mode than in the online setting. The performance gap between the two settings maximizes when context length is around 75, and vanishes with long (\(> 150\)) or short (\(< 20\)) context windows. We surmise that for long (\(> 150\)) context window, the preceding context information might already be adequate for detection, while for short (\(< 20\)) context windows, the context, regardless whether it is unidirectional or bidirectional, might not contain enough information for detection.

7 Related Work

**Reference-based Hallucination Detection** Apart from human verification (Chen and Bansal, 2018), researchers have developed effective reference-based methods which automatically detect hallucination in the generated text using statistical n-gram matching (Dhingra et al., 2019; Liu et al., 2019), edit distance heuristics (Zhou et al., 2020), natural language inference (Kryscinski et al., 2020; Falke et al., 2019), information extraction (Zhang et al., 2020; Goodrich et al., 2019) or question answering (Scialom et al., 2019; Eyal et al., 2019; Wang et al., 2020a). Our approach differs from them in that we investigate the reference-free hallucination detection scenario.

To reduce hallucinations in the reference-based setting, researchers have applied iterative training (Nie et al., 2019), post editing (Dong et al., 2020), soft constraints, e.g. attention manipulation (Kiddon et al., 2016; Hua and Wang, 2019; Tian et al., 2019; Liu et al., 2019) or optimal transport (Wang et al., 2020b), and template/scaffold guided schema (Liu et al., 2017; Wiseman et al., 2018; Moryossef et al., 2019; Ye et al., 2020; Shen et al., 2020; Li and Rush, 2020; Balakrishnan et al., 2019; Du et al., 2020; Liu et al., 2021).

**Reference-free Detection Approaches** Reference-free hallucination detection is closely related to fake news detection (Zellers et al., 2019; Zhou and Zafarani, 2020; Zhong et al., 2020), which aims to identify deliberate disinformation in a reference-free manner on social media and usually involves common-sense and world knowledge reasoning (Monti et al., 2019), or fact checking (Thorne et al., 2018), where practitioners are asked to verify given claims without references by retrieving related evidence from Wikipedia. Another line of research is to classify sentence-level language specificity (Li and Nenkova, 2015; Gao et al., 2019), which scales from 1 (very general) - 5 (very specific) for short text, e.g. tweets, according to human annotation.

The proposed hallucination detection aims to examine the text in a finer granularity than fake news detection and fact checking. In the proposed task, most parts of the text remain faithful; our goal is to identify subtle hallucinations at the token-level. Fake news detection or specificity assessment, on the other hand, usually focus on sentence- or document-level detection.

8 Conclusions

We have proposed a token-level reference-free hallucination detection task and introduced a benchmark dataset HADES for identifying with fine granularity hallucination in free-form text generation. To create this dataset, we perturbed texts to simulate hallucination in NLG system, and performed an iterative model-in-the-loop annotation approach to annotate the perturbed text in an imbalanced label scenario. We have further provided comprehensive analyses of HADES and evaluated several baseline models to establish initial bench-
marks. We hope that the proposed task and dataset will shed light on high-resolution hallucination detection in free-form text generation and will eventually lead to real-time hallucination prevention.

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Appendix for Token-level Reference-free Hallucination Detection
Benchmark for Free-form Text Generation

A Detailed Statistical Analysis
In Table 4, we provide detailed statistical analyses for different POS and NER tags in the HADES dataset. Although the average word probability and average word entropy features differ among POS/NER tags, hallucinated content typically associates with higher word probability and word entropy irrespective of POS/NER tag. Strong correlation between hallucination labels and TF-IDF or PPMI features is not observed.

B Annotation Interface
The annotation interface is provided in Fig 6.

C Subsampling Ratio For Label Rebalance
We adopt an iterative model-in-the-loop method in data annotation. Since observe a label imbalance between “hallucination” (H) and “not hallucination” (N) in the initial rounds of annotation, we employ subsampling to rebalance the label distribution in Sec 3.3. We accumulate the data annotated in the all previous rounds, and train a detection model using the accumulated data. Then we apply the detection model to the unannotated data in the candidate data pool in order to select next batch of data as elaborated in Sec 3.3.

We assume that the human annotation for H and N cases is the oracle, indicating actual H/N. Since the actual “hallucinated” is dominant, we try to subsample from the instances that are predicted as H from the detection model (TP + FP) with a subsampling ratio s, so that the actual H (TP + FN) is roughly equal to actual N (FP + TN) after the resampling. We denote TP and TN as x and y and represent FN and FP with x, y, α, γ, β:

\[ FN = \frac{1 - \alpha}{\alpha} x \quad (5) \]

\[ FP = \frac{1 - \beta}{\beta} y \quad (6) \]

By substituting FN, FP into Eq. (4), we have:

\[ \gamma = \frac{x}{x + \frac{1 - \beta}{\beta} y} \quad (7) \]

To make the distribution of actual H/N even (sTP+FN=sFP+TN), we have:

\[ sx + \frac{1 - \alpha}{\alpha} x = s \frac{1 - \beta}{\beta} y + y \quad (8) \]

By combining Eq. (7) and Eq. (8), we figure out the optimal subsampling ratio \( s^* \).

\[ s^* = \frac{-2 \alpha \beta \gamma + \alpha \beta + \beta \gamma + \alpha \gamma - \gamma}{(2 \gamma - 1) \alpha (1 - \beta)} \quad (9) \]

Where TP, FP, TN, FN are the abbreviations of “true positive”, “false positive”, “true negative” and “false negative” cases. We aim to subsample from the instances that are predicted as H from the detection model (TP + FP) with a subsampling ratio s, so that the actual H (TP + FN) is roughly equal to actual N (FP + TN) after the resampling. We denote TP and TN as x and y and represent FN and FP with x, y, α, γ, β:

\[ FN = \frac{1 - \alpha}{\alpha} x \quad (5) \]

\[ FP = \frac{1 - \beta}{\beta} y \quad (6) \]

By substituting FN, FP into Eq. (4), we have:

\[ \gamma = \frac{x}{x + \frac{1 - \beta}{\beta} y} \quad (7) \]

To make the distribution of actual H/N even (sTP+FN=sFP+TN), we have:

\[ sx + \frac{1 - \alpha}{\alpha} x = s \frac{1 - \beta}{\beta} y + y \quad (8) \]

By combining Eq. (7) and Eq. (8), we figure out the optimal subsampling ratio \( s^* \).

\[ s^* = \frac{-2 \alpha \beta \gamma + \alpha \beta + \beta \gamma + \alpha \gamma - \gamma}{(2 \gamma - 1) \alpha (1 - \beta)} \quad (9) \]

10 Defining H as the positive class.
| Tag       | Word Prob($\times 10^{-8}$) | Entropy | TF-IDF         | PPMI         |
|-----------|-----------------------------|---------|----------------|--------------|
|           | $H$                         | $N$     | $H$            | $N$          | $H$            | $N$          |
| POS:NOUN  | $6.98_{12.0}$               | $1.68_{63.4}$ | $2.75_{15.2}$ | $1.86_{13.13}$ | $0.25_{0.021}$ | $0.23_{0.018}$ | $0.213_{1.145}$ | $0.228_{1.140}$ |
| POS:VERB  | $2.51_{0.33}$               | $0.69_{2.89}$ | $2.25_{1.25}$ | $1.76_{1.00}$ | $0.19_{0.012}$ | $0.18_{0.011}$ | $0.206_{1.112}$ | $0.216_{1.19}$  |
| POS:ADJ   | $8.16_{44.8}$               | $2.86_{18.9}$ | $2.95_{1.46}$ | $2.38_{1.23}$ | $0.21_{0.017}$ | $0.17_{0.009}$ | $0.180_{1.128}$ | $0.164_{1.117}$ |
| POS:ADV   | $5.13_{14.2}$               | $2.65_{12.2}$ | $2.56_{1.18}$ | $1.97_{1.09}$ | $0.16_{0.011}$ | $0.14_{0.008}$ | $0.181_{1.114}$ | $0.182_{1.105}$ |
| POS:PROPN | $14.3_{33.6}$               | $4.35_{17.8}$ | $3.12_{1.73}$ | $1.56_{1.39}$ | $0.29_{0.026}$ | $0.03_{0.029}$ | $0.198_{1.150}$ | $0.312_{2.75}$  |
| POS:other | $9.56_{11.1}$               | $3.28_{15.7}$ | $2.64_{1.61}$ | $1.26_{0.97}$ | $0.13_{0.013}$ | $0.11_{0.010}$ | $0.158_{1.07}$  | $0.205_{0.92}$  |
| NER:null  | $5.37_{25.6}$               | $1.24_{19}$ | $2.52_{1.47}$ | $1.79_{1.06}$ | $0.21_{0.019}$ | $0.019_{0.014}$ | $0.200_{1.132}$ | $0.215_{1.126}$ |
| NER:other | $8.43_{25.4}$               | $5.06_{21.5}$ | $2.93_{1.56}$ | $1.65_{1.44}$ | $0.23_{0.023}$ | $0.026_{0.024}$ | $0.189_{1.146}$ | $0.263_{2.37}$  |
| All       | $5.85_{25.6}$               | $1.30_{7.6}$ | $2.58_{1.49}$ | $1.78_{1.07}$ | $0.21_{0.019}$ | $0.019_{0.014}$ | $0.198_{1.144}$ | $0.216_{1.129}$ |

Table 4: Detailed statistical features ($\text{Mean}_{\text{std}}$) for “hallucinated” ($H$) and “not hallucinated” ($N$) cases.