

Unsupervised and Distributional Detection of Machine-Generated Text

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Abstract

The power of natural language generation models has provoked a flurry of interest in automatic methods to detect if a piece of text is human or machine-authored. The problem so far has been framed in a standard supervised way and consists in training a classifier on annotated data to predict the origin of one given new document. In this paper, we frame the problem in an *unsupervised* and *distributional* way: we assume that we have access to a large collection of unannotated documents, a big fraction of which is machine-generated.

We propose a method to detect those machine-generated documents leveraging repeated higher-order n -grams, which we show over-appear in machine-generated text as compared to human ones. That weak signal is the starting point of a self-training setting where pseudo-labelled documents are used to train an ensemble of classifiers.

Our experiments show that leveraging that signal allows us to rank suspicious documents accurately. Precision at 5000 is over 90% for top- k sampling strategies, and over 80% for nucleus sampling for the largest model we used (GPT2-large). The drop with increased size of model is small, which could indicate that the results hold for other current and future large language models.

1 Introduction

The introduction of powerful neural left-to-right language models in the last few years has revolutionized the capacity to automatically generate human-like text. Their power has grown proportionally to the worry that those models could be used to generate *fake* documents,¹ either news articles (Zellers et al., 2019), comments (Yang et al., 2019) or other type of text (Buchanan et al., 2021) without revealing the non-human authorship of it.

¹referring here to machine-generated text as opposed to text containing objectively false statements

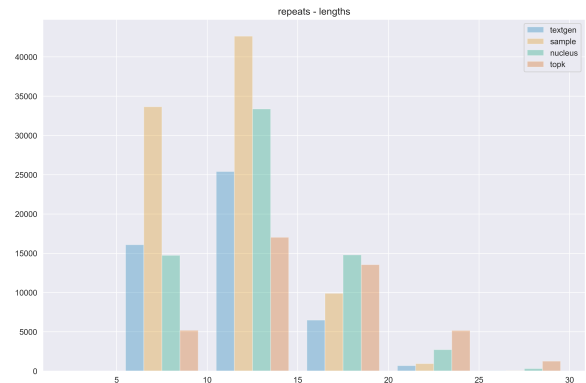


Figure 1: Histograms of the lengths of super-maximal repeats occurring in each dataset. `textgen` refers to human generated text.

Recently, a number of papers have investigated the capacity of humans and learning algorithms to determine if a given text is human or machine generated (Ippolito et al., 2020; Dugan et al., 2020; Maronikolakis et al., 2020). However, so far all those methods are making two key assumptions: (i) the settings is framed in a supervised way for the machine learning methods, having access at training time to machine-generated samples from the same generator; (ii) the decision is done for each sample individually and independently.

In this paper, we argue that this is not realistic.

On one side any ill-intended adversary would take care of either retraining its own model, or modifying the generation in such a way as to drift significantly the distribution of generated text. This can easily be done by using different sampling strategies (Choi et al., 2020; Welleck et al., 2020; Holtzman et al., 2020; Massarelli et al., 2020), an a-posterior re-weighting strategy or the use of one of a number of controlled generation methods currently available (Dathathri et al., 2020; Khalifa et al., 2020). More-over, the domain used to train such a classifier might be different from the one where it is deployed. Bakhtin et al. (2021) studied

this precise setting and showed that the quality of a human/machine discriminator degraded quickly when the prompts used to generate text were from a different domain. On the other side, the problem of determining the origin of one fixed document is in most use cases not the real problem. As an example, an article generated by an existing template-based data-to-text method (Reiter and Dale, 2000) is arguably of less concern than an article diffusing false information written by a human author. Indeed, one danger of the current language models lies in their capacity of generating a huge amount of human-like text but biased towards a desired opinion or topic (Leroux, 2020; Buchanan et al., 2021).

We therefore frame the problem of detecting machine-generated texts as follows: given a set of documents, and the suspicion that a large fraction of them is generated by machine; is it possible to detect those? The departure of this setting from the current one is in defining it in a *distributional and unsupervised way*.

This setting is complicated by the fact that modern language models coupled with current decoding strategies follow very closely the statistics of generated tokens. The key insight of our approach is that, while unigram frequency appears indistinguishable from human generated text, the same is not true for higher-level n -grams. In particular, the distribution of repeats present in the machine-generated text is quite different, as shown in Fig. 1. While there is apparently nothing special in those repeats (see some examples in Fig. 2) and they might pass absolutely undetectable when analyzing a single document, they become apparent when looking at a large sample. Thus, we leverage this signal to pseudo-label the input documents and train an ensemble of classifiers on them. Our experiments show that a majority vote of these classifiers achieves over 90% precision at 5 000 when generating from GPT2-large using `top-k` sampling, and over 80%, for `nucleus` sampling.

2 Related Work

The capacity of large pretrained (Mikolov et al., 2013; Devlin et al., 2018) Transformer (Vaswani et al., 2017) models trained only with a cross-entropy loss (Brown et al., 2020) are transforming what is possible with natural language processing techniques. Out of the risks that those models pose (Bender et al., 2021) here we are interested

in their possibility of generating text which appears as human-generated but without revealing the true authorship. While those models do commit errors – Dou et al. (2021) enumerates and analyses 10 types – they are surprisingly low and often hidden under otherwise very fluent language. This has created a large line of work that tackles the problem of discriminating such documents, as surveyed in Jawahar et al. (2020). In their initial release strategy (Solaiman et al., 2019) OpenAI already mentioned approaches to use the same generation models to identify a text generated with that model, both through fine-tuning on annotated data as well as in a zero-shot setting, using the underlying probabilities. Ippolito et al. (2020) show that an automatic classifier can detect statistical patterns of the generated document and obtains an accuracy for short documents (60 tokens) between 70 and 90% depending on the decoding strategy. Surprisingly, their performance is different than that of humans, which have a harder time picking up those statistical signals but are unbeaten so far when recognizing incoherence or factually wrong statements. Maronikolakis et al. (2020) obtains a similar conclusion that automatic models are better than humans for detecting fake headlines. Studying the performance of automatic classifiers, Bakhtin et al. (2021) provide an exhaustive analysis varying generator and discriminator architecture as well as training data, concluding that performance of the discriminator is high if it is trained on data from the same domain. However, any domain shift affects it in a severe way. Dugan et al. (2020) focuses specifically on the problem of detecting the boundary, from which moment the human generated prompt stops and the machine-written text starts. The fact that pre-trained language models have statistical patterns which differ from human-generated text has been used in the past not only as feature for detection, but also as input for the interactive tool GLTR (Gehrmann et al., 2019). This tool relies on the probability distribution as given by an inspection model: the case study detailed there shows that even when that inspection model is different than the generation model (although it is of the same family, different sizes of GPT2 to be precise) the highlighted patterns help humans detect the authorship. It stops however at unigram features as well. The concurrent work of Uchendu et al. (2021) proposes a dataset of human and machine-generated samples, across a variety of models, and

also frame the problem as authorship attribution. The proposed baselines are all supervised however, although the authors perform a stylistometric analysis, concluding the need “to develop a model that unearth more subtle yet distinct patterns”.

All those studies focus on asking (crowd-sourced) human annotators to decide if a text was generated by a machine or a human. [Clark et al. \(2021\)](#) points out that the high fluency of modern generation models, combined with a generally low expectation of what machines can accomplish, makes it hard to make this distinguished, even for lightly trained annotators.

3 Background

Modern language models are trained through maximum likelihood estimation. Inferring new sequences is done in an auto-regressive manner, where each token’s probability is estimated as a function of its previous context. Greedy decoding – this is, picking the most probable token – is rarely used in open-ended generation. Similarly, using the probability distribution directly to sample from it is also seldom used: while it mimicks the unigram distribution of tokens very accurately, it often generates incoherent text and makes it therefore easy for humans to detect ([Ippolito et al., 2020](#)). The two most used decoding strategies reduce the universe of possible tokens: `top-k` ([Fan et al., 2018](#)) which samples from the k most probable words, and `nucleus` sampling ([Holtzman et al., 2019](#)) which samples from the tokens making up the top p probability mass. Formally, let us assume c is the prefix of fixed windows-size, and which is initially human-written (the prompt) but then gets extended with the generations so far. $P(\cdot|c)$ is the probability distribution over the vocabulary of tokens V of the language-model, given the context c . These decoding strategies then sample from a re-normalized distribution which modifies the support: instead of being all of V , only the most probable tokens are considered. This is, we sort all tokens $x^{(1)}, x^{(2)}, \dots, x^{(|V|)}$ according to their probability: $P(x^{(1)}|c) > P(x^{(2)}|c) > \dots > P(x^{(|V|)}|c)$, and define then:

$$P_{topk}^k(x^{(i)}|c) = \begin{cases} \frac{P(x^{(i)}|c)}{Z} & \text{if } i \leq k \\ 0 & \text{otherwise} \end{cases}$$

$$P_{nuc1}^p(x^{(i)}|c) = \begin{cases} \frac{P(x^{(i)}|c)}{Z} & \text{if } \sum_{j=1}^i P(x^{(j)}) \leq p \\ 0 & \text{otherwise} \end{cases}$$

where Z denotes the respective normalization constant, and k and p are respective constant which control the sparsity of the support.

4 Method

It is well known that current language models trained on large-scale data allow for generation whose individual token probability mimics very closely that of human-generated text. For example, a frequency-rank plot of text obtained through ancestral or nucleus sampling is almost indistinguishable from that of human text (the famous “Zipf Law”) ([Holtzman et al., 2020](#), Figure 7).

However, the same does not happen for higher-order n -grams. Fig. 1 shows a histogram of the length of so-called super-maximal repeats² ([Gusfield, 1997](#)) for a set of documents generated by each strategy. Specifically, we consider equivalent sets of documents, where each set is generated using one decoding strategy over a language model, or sampled from human texts (details in Sect. 5). The repeats are then computed on each set independently. As can be seen from Fig. 1, ancestral sampling produces a much larger number of super-maximal repeats. More interestingly, `nucleus` sampling not only follows a similar trend of producing more repeats, but that difference gets larger for longer repeats. Any individual such repeat can hardly be considered a signal of being machine-generated: in Fig. 2 we depict some examples. However, from this analysis it appears that they are much more likely to occur in machine-generated text than in a human one.

Starting from this analysis, we propose a method to detect machine-generated documents in a large collection, based on a self-training approach. Pseudo-code of this algorithm is shown in Alg. 1.

Given the full collection of documents, we first compute the full set of super-maximal repeats. A repeated substring r is super-maximal with respect to a collection of documents if r does not occur in any other repeated substring of this collection.

²A repeated substring r is super-maximal with respect to a collection of documents if there is no other repeat that contains r .

I could hardly tell what
 In the latter part of the
 an important figure in the
 that it is impossible for
 they had nothing to do with
 for long periods of time.

Figure 2: Examples of super-maximal repeats occurring at least 3 times in the set of documents generated with `nucleus` sampling.

Their number (and their number of occurrences) is linear in (and even bounded by) the combined length of all documents. They can be computed efficiently in linear time with respect to the total length of the collection using a suffix-tree-like data structure (Gusfield, 1997), taking advantage of the fact that r is *not* super-maximal if it can be extended at either side by some symbol and still be a repeated substring: if there is a character a such that $a.r$ or $r.a$ is also repeated, then r is not super-maximal. In our experiments we used a more memory efficient variation, based on a suffix array (Manber and Myers, 1993), which in combination of the “longest common prefix” (LCP) array allows for fast computation of repeats (Abouelhoda et al., 2004). Their computation is very fast and only takes a few seconds even for the largest of the collections we consider.

Here we used super-maximal repeats that occur at least 3 times (to reduce inclusions of spurious repetitions), and have at least 20 characters. Note that they are computed on the non-tokenized, raw text and might therefore span several tokens. Those values were fixed very early on in our experiments, and we did not modify or optimize them further.

A random subset of repeats are then used in order to pseudo-label documents containing those repeats as machine-generated. The same amount of human-generated documents are then selected. We explore two scenarios (which impact line 6 of Alg. 1): one fully unsupervised, where that selection is noisy, picking from the full collection (and therefore incurring in a 50% mislabeling rate for the negative examples) and one where a separate collection of human text exists. This pseudo-annotated dataset is then fed as input to a binary classifier. The set of documents on which this classifier is trained is reduced (maximal 60 documents, assuming that each occurrence of each of the 20 repeats occurs in a different document), so we repeat this process K

times. The final raking is obtained by simply summing the predictions of each individual classifier: each document in the dataset is ranked according to the amount of time it was predicted to be machine-generated.

Algorithm 1 Detection of machine-generated documents using repeats.

```

1: function DETECTION(document set  $D$ , # of
   models  $K$ )
2:   repeats  $\leftarrow$  supermaximal( $D$ , minLen,
   minOcc)
3:   for  $k \in [1 \dots K]$  do
4:     subset  $\leftarrow$  random.choice(repeats, 20)
5:     pos  $\leftarrow$   $\{d \in D : \exists r \in \text{subset} : r \in d\}$ 
6:     neg  $\leftarrow$  random.choice( $D$ ,  $|\text{pos}|$ ) // we
   also experiment using true human text
7:      $\text{clf}_k \leftarrow \text{train}(\text{pos}, \text{neg})$ 
8:   end for
9:    $\text{score}_d \leftarrow \sum_{k=1}^K \text{clf}_k(\text{machine}|d) >$ 
    $\text{clf}_k(\text{human}|d) \forall d \in D$  return sort(score)
10: end function

```

5 Experiments

For the language generator, we decided to use a decoder-only architecture due to its faster inference speed (as opposed to a sequence-to-sequence model like for example T5 (Raffel et al., 2020)). Because of the large number of generations we needed for these experiments (over 300 000 sequences of up to 512 tokens) it was unfeasible to use GPT-3, which at the moment of writing was only accessible through a paid API. We therefore settled on the largest decoder-only model that could be run on premises: GPT-2, accessed through HuggingFace’s Transformers library (Wolf et al., 2020). In order to estimate the evolution of our metrics with increasing model size we used various model. The main experiments were done with the following decoding algorithms: `topk` ($k=10$) and `nucleus` sampling ($p=0.8$), and other analysis used greedy decoding and ancestral sampling.

We downloaded the top 100 books from the Gutenberg Project, according to their Frequently Viewed page³ on July 27, 2020, extracted their content and split the texts in paragraphs, keeping

³<https://www.gutenberg.org/browse/scores/top>

only the ones with at least 100 characters. From there we extracted as prompt the two first sentences of each paragraph. The continuation was used as human generation (`textgen`).

The final dataset was composed therefore of continuations of those discarded prompts. To control for length, we filtered out generations with less than 300 characters and we trimmed the generated text after the 300th character. The resulting continuations (between 30k and 34k, depending on the model version) were split evenly to obtain a dataset of machine generated and human continuations. This is, for one given prompt its possible continuations (either human or machine-generated) appears only once.

We derive from this dataset two different settings: One, **semi-supervised**, in which we keep 5% of human-generated documents as negative examples, and another one, fully **unsupervised**, in which negative samples are chosen at random (and thus, have a 50% error rate).

Super-maximal repeats were computed on the joint remaining documents, combining both human and machine-generated text. To produce pseudo-labels of machine-generated text we used super-maximal repeats that are longer than 20 characters and occur at least 3 times, and trained classifiers using a distilled BERT model as provided by HuggingFace (Wolf et al., 2020).⁴ We kept those values fixed across all experiments.

Here we report results in 6 settings, corresponding to 3 model sizes (corresponding to GTP-2 released model sizes of - respectively - 124M, 355M and 774M parameters) and 2 sampling strategies (`topk` and `nucleus`).

For evaluation, we assume a scenario where our proposed method would be deployed in a semi-automatic system where human annotators would receive a batch of suspicious documents to revise. This is similar to how current detection of ambiguous and sensitive content is handled (such as fake news or hate speech). In such a scenario, the accuracy of the final method is of less importance than its capacity to propose a set with high precision of machine generated text. We therefore take metrics from information retrieval, in particular *precision at m* which is the amount of documents that were correctly labeled as machine-generated in the first m documents, when sorting them according to their final score.

⁴`class DistilBertForSequenceClassification.`

6 Results & Analysis

In Fig. 5 we report values for *precision at m* for the **semi-supervised** scenario. The documents are sorted according to the number of times individual experts voted that document to be machine-generated, and we show the results with increasing number of such experts (from 10 to 100). As can be seen, `nucleus` sampled text is harder to detect than `top-k`, something that confirms the literature.

While there is a clear difference with different sampling techniques, larger models are not always harder to detect than smaller ones, and the final numbers are very close between GPT2-medium and GPT2-large. Note that in almost all cases, the precision at 5 000 remains higher than 80% using 30 or more experts, and is close to 100% for `topk`.

Finally, Fig. 6 reports the same results when using noisy data not only for machine generated but also for human-generated documents. This follows the **unsupervised** scenario where no other in-domain human generated text is available. While the numbers are significantly lower, the precision at m remains high for `topk`, and is around 80% for `nucleus` sampling on GPT2-large for the first 100 documents.

In Fig. 3 and 4 we show – respectively – correct and incorrect examples of the top-25 documents obtained through `nucleus` sampling on GPT2-Large, using noisy labels for the human-generated text (the case of Fig. 6). Fig. 3 are indeed machine-generated, while Fig. 4 are human-generated and therefore wrongly retrieved. Given an individual example, there does not seem to be nothing apparent which would allow to judge on their origin. It is the distributional approach that obtains a signal by looking at a large collection of such documents.

6.1 Ablating pseudo-relevance loop

The use of repeats to capture a weak signal raises the question if the pseudo-relevance step is necessary, or if classifying all those documents that contain a supermaximal repeat is not a good enough baseline. A first issue is that such a setting does not allow for fine-grained scoring: in all the datasets no document contained more than one supermaximal repeat. Precision at m is therefore not applicable, as the sorting only throws documents into two bins, depending if they contain or not such a repeat.

In Table 1 we report the percentage of machine-generated documents out of all those that contain

"Oh, you're a dry journalist," Miss Shelton remarked. "You wouldn't understand, are you?" "No, I won't understand," Albert responded. "Ah," Miss Shelton said. "I don't think so." "I'm quite right. We've worked up a bit of hostility, the past couple of months, so you wouldn't be able to understa
Our attention, therefore, may, with some propriety, be drawn to the inconveniences which are caused by the coming into contact of many members of a particular family, in consequence of intermarriage, according to one particular, and the infusion into it of a fatal mixture; which, in a time of incre
In this sense there are few facts more striking than that human race has been spread over a number of different regions of the globe from two widely separated periods of natural history, of which both appear to have been limited by natural resources. From what is now South America to Africa is not
They went out, turned down the staircase, and into the gardens, and drew up the stones, prepared a rug. Rostov put on his usual shirt, pocket-handkerchief, hat, coat, shoes, and went to bed. II It was only late in the night, and the moon was quite high, that Rostov's uncle sent for him. When he r
And his plan was laid before me: it was that when I rose the dance-shoppe would be empty of men; the new moon would no longer be a sign of opportunity to exercise its power of purifying it; and I should break the hearts of the children of thy sister. My hands trembled before the dread of a word whi

Figure 3: Examples of sentences that were classified **correctly** as machine-generated, from the top-25 generations with nucleus sampling using GPT2-Large.

At length the breathless hunter came so nigh his seemingly unsuspecting prey, that his entire dazzling hump was distinctly visible, sliding along the sea as if an isolated thing, and continually set in a revolving ring of finest, fleecy, greenish foam. He saw the vast, involved wrinkles of the slig
Night was coming on, so I left the river, and went into a thicket, where I covered myself all over with leaves, and presently heaven sent me off into a very deep sleep. Sick and sorry as I was I slept among the leaves all night, and through the next day till afternoon, when I woke as the sun was we

Figure 4: Examples of sentences that were classified **incorrectly** as machine-generated, from the top-25 generations with nucleus sampling using GPT2-Large (this is, these are human-generated).

decoding	model	prec@ m	m
nucleus	small	60.3	5 745
	medium	58.0	4 705
	large	57.6	4 856
top- k	small	75.0	9 095
	medium	71.7	7 049
	large	71.3	7 208

Table 1: Precision at m values by classifying all documents containing super-maximal repeats as machine-generated.

supermaximal repeats, for the various combination of decoding algorithm and model size. In all cases those numbers are lower than what can be obtained after training a classifier on those documents (Fig. 5 and 6) pointing towards a better discrimination power by going through an additional classifier step. For example, for nucleus sampling the percentage of documents containing a supermaximal repeat that are machine-generated is around 60%, while it is over 80% with the additional classification step in the weakly supervised case (and around 70% for comparable values of m in the unsupervised one). A similar absolute difference – for higher values – can be observed for top- k sampling.

6.2 Full Classification

The approach described so far permits a semi-automatic human-in-the-loop system, where the classifier selects highly probable documents for further human inspection. However, the self-training approach can be pushed even further, to train a classification model that aims to classify the whole data-set. A standard approach in information retrieval to enrich the queries is *pseudo-relevance feedback*: given a query, this approach assumes that the top-most documents are relevant. A second query is then created, which takes the original one and enriches the query with terms from those top-ranked documents. The intuition is that those alternative terms allow for richer information and might capture documents that would otherwise be missed.

Inspired by this, we aim to train a classifier that uses the top ranked documents of Alg. 1 and measure its accuracy on a fixed held-out data-set. In Fig. 7 we plot the resulting accuracies with increasing number of training data. To create this pseudo training data we use again gold human-generated documents, while documents labelled as machine

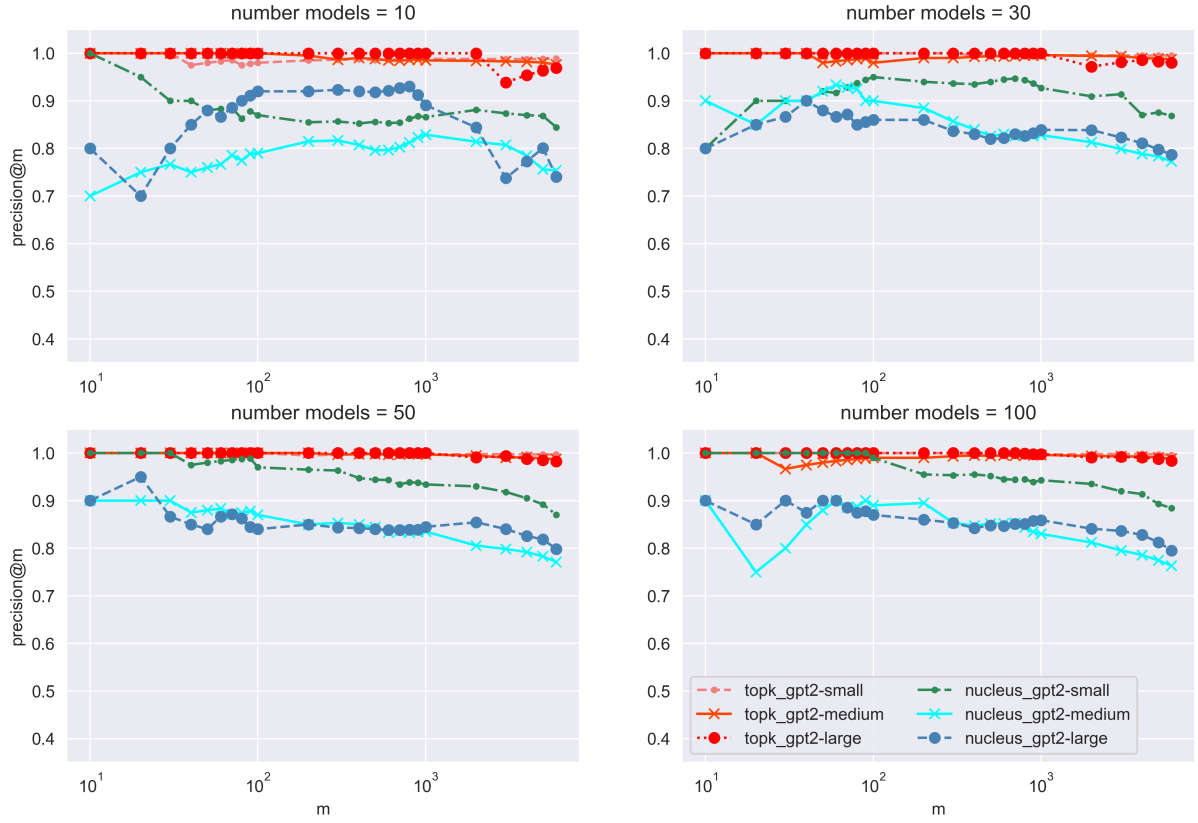


Figure 5: Precision at m for various models and two sampling strategies on the semi-supervised scenario.

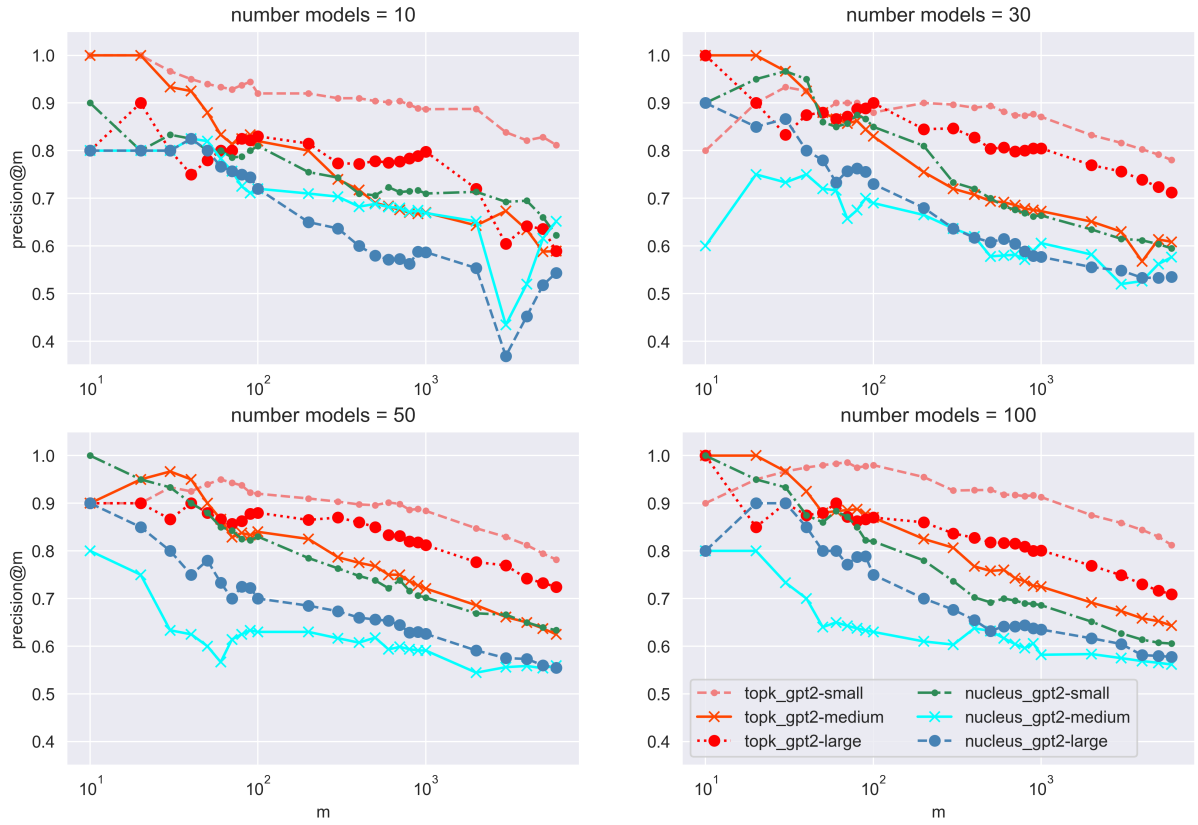


Figure 6: Precision at m for various models and two sampling strategies in the fully unsupervised scenario.

generated are the top ranked documents by the semi-supervised approach of Sect. 4. The dataset here is obtained with GPT2-medium. As comparison, we also report the results obtained with a fully supervised model on the same test data and the same number of training data. The gap between the fully supervised and semi-supervised approaches is high for both decoding strategies. However, the semi-supervised system only had gold labels for human-generated text and all the machine-generated labels were inferred from the data.

7 Discussion

Why does this work at all? Existing zero-shot detection approaches, like the analysis done with 1.5B-GPT2 of Solaiman et al. (2019) or the GLTR interactive tool (Gehrmann et al., 2019), rely on the probabilities obtained by an inspection models, which in most cases have some familiarity with the generation model. The close distribution of unigram frequencies of generated text might indicate that modern language models do not seem to have a clear statistical signature, a reason why the text generated by them is often hard to detect with classifiers.

However, the results in this work seem to indicate that those patterns are still present, but at the level of repetitions. Assuming that the language models is one author, this work can be seen as detecting the single author who generated 50% of the dataset. The fact that this is (somehow) possible could be an indication that the prompt is not suffi-

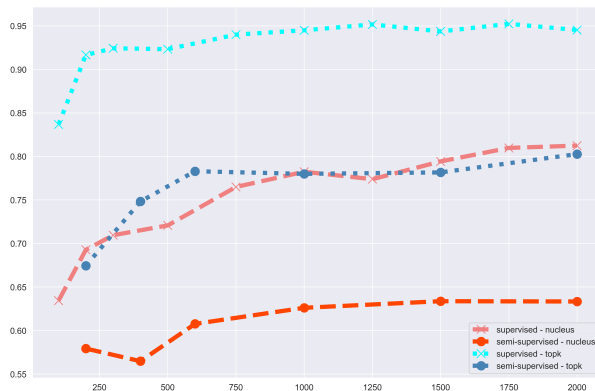


Figure 7: Self-supervised (only using human-generated texts) approach for a classifier, compared to a fully supervised approach. The semi-supervised approach used $K = 10$, and in all cases the text was generated by GPT2-Medium and the binary classifier is a fine-tuned distilled BERT model.

cient for the language-model to mimic the original author’s style, and that some of its own style – evidenced by the repetition of some phrases – becomes apparent. Further studies in the stylometry of the generated text and how this relates to the length and type of the prompt might provide more insights into the limitations and adaptability of large-scale language models.

Another related cause might be due to the *diversity* of the generated text. Fig. 8 plots the relative histogram of the diversity, measured as the number of different words divided by the number of tokens in the document. As is well-known, greedy produces unvarying continuations and is prone to repetitions. The other sampling techniques have a much closer distribution to human text (`textgen`). Human text, however, is less peaked than the sampling strategies, including ancestral sampling (`sample`) which – in average – produces even more diverse text. That diversity has a direct impact on the number of repetitions: a collection of documents with lower diversity is more probable to give rise to longer repetitions. This might be another reason why `top-k` and `nucleus` have a larger set of such long repetitions. Moreover, note that the detection accuracy is higher for `top-k` than for `nucleus`, something that correlates with their diversity.

8 Conclusion & Limitations

We analyzed characteristics of machine-generated text, detecting that they tend to generate certain (well-formed) phrases more often than in human text. Using that signal as an input to a series of classifier our experiments shows that this signal can be amplified to allow to rank documents in such a way that machine generated documents tend to appear in the beginning. A limitation of this work is the balanced assumption of the training set, as well as the somehow rigid nature of exact repeats (which does allow fast computation however). We believe that further stylometric analysis of generated text of such models could allow to provide additional warning signals that machine-generated content is flooding a certain corpus and even identify examples of such documents.

References

Mohamed Ibrahim Abouelhoda, Stefan Kurtz, and Enno Ohlebusch. 2004. Replacing suffix trees with

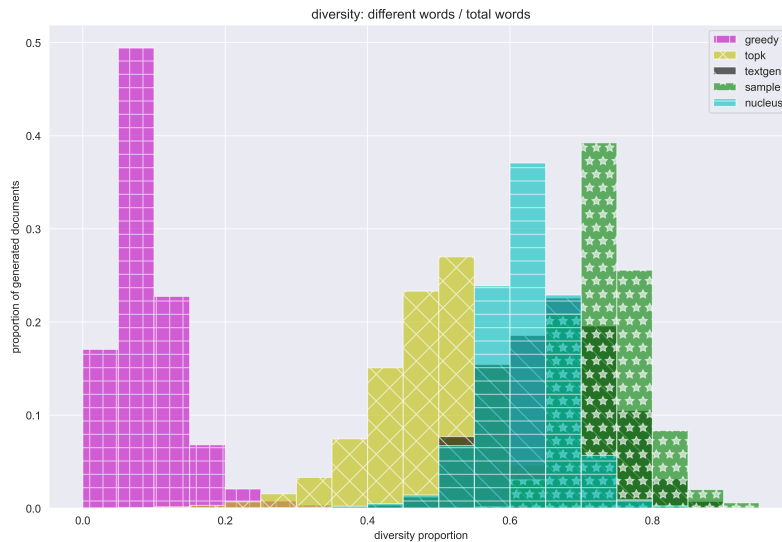


Figure 8: Histogram of diversity for different sampling strategies.

- enhanced suffix arrays. *Journal of discrete algorithms*, 2(1):53–86.
- Anton Bakhtin, Yuntian Deng, Sam Gross, Myle Ott, Marc’Aurelio Ranzato, and Arthur Szlam. 2021. [Residual energy-based models for text](#). *Journal of Machine Learning Research*, 22(40):1–41.
- Emily M Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. On the dangers of stochastic parrots: Can language models be too big. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency; Association for Computing Machinery: New York, NY, USA*.
- Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*.
- Ben Buchanan, Andrew Lohn, Micah Musser, and Katerina Sedova. 2021. Truth, lies, and automation: How language models could change disinformation.
- Byung-Ju Choi, Jimin Hong, David Park, and Sang Wan Lee. 2020. [F²-softmax: Diversifying neural text generation via frequency factorized softmax](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9167–9182, Online. Association for Computational Linguistics.
- Elizabeth Clark, Tal August, Sofia Serrano, Nikita Haduong, Suchin Gururangan, and Noah A. Smith. 2021. All that’s ‘human’ is not gold: [Evaluating human evaluation of generated text](#). In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 7282–7296, Online. Association for Computational Linguistics.
- Sumanth Dathathri, Andrea Madotto, Janice Lan, Jane Hung, Eric Frank, Piero Molino, Jason Yosinski, and Rosanne Liu. 2020. [Plug and play language models: A simple approach to controlled text generation](#). In *International Conference on Learning Representations*.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.
- Yao Dou, Maxwell Forbes, Rik Koncel-Kedziorski, Noah A Smith, and Yejin Choi. 2021. Scarecrow: A framework for scrutinizing machine text. *arXiv preprint arXiv:2107.01294*.
- Liam Dugan, Daphne Ippolito, Arun Kirubakaran, and Chris Callison-Burch. 2020. Roft: A tool for evaluating human detection of machine-generated text. *arXiv preprint arXiv:2010.03070*.
- Angela Fan, Mike Lewis, and Yann Dauphin. 2018. Hierarchical neural story generation. *arXiv preprint arXiv:1805.04833*.
- Sebastian Gehrmann, Hendrik Strobelt, and Alexander Rush. 2019. [GLTR: Statistical detection and visualization of generated text](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 111–116, Florence, Italy. Association for Computational Linguistics.
- Dan Gusfield. 1997. Algorithms on stings, trees, and sequences: Computer science and computational biology. *Acm Sigact News*, 28(4):41–60.
- Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2019. The curious case of neural text degeneration. *arXiv preprint arXiv:1904.09751*.

- Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2020. [The curious case of neural text de-generation](#). In *International Conference on Learning Representations*.
- Daphne Ippolito, Daniel Duckworth, Chris Callison-Burch, and Douglas Eck. 2020. [Automatic detection of generated text is easiest when humans are fooled](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1808–1822, Online. Association for Computational Linguistics.
- Ganesh Jawahar, Muhammad Abdul-Mageed, and Laks Lakshmanan, V.S. 2020. [Automatic detection of machine generated text: A critical survey](#). In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 2296–2309, Barcelona, Spain (Online). International Committee on Computational Linguistics.
- Muhammad Khalifa, Hady Elsahar, and Marc Dymetman. 2020. A distributional approach to controlled text generation. *arXiv preprint arXiv:2012.11635*.
- Hugo Leroux. 2020. Trump ou Biden : l’intelligence artificielle a-t-elle joué un rôle dans l’élection américaine ? *Science et Vie*.
- Udi Manber and Gene Myers. 1993. Suffix arrays: a new method for on-line string searches. *siam Journal on Computing*, 22(5):935–948.
- Antonis Maronikolakis, Mark Stevenson, and Hinrich Schutze. 2020. Transformers are better than humans at identifying generated text. *arXiv preprint arXiv:2009.13375*.
- Luca Massarelli, Fabio Petroni, Aleksandra Piktus, Myle Ott, Tim Rocktäschel, Vassilis Plachouras, Fabrizio Silvestri, and Sebastian Riedel. 2020. [How decoding strategies affect the verifiability of generated text](#). In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 223–235, Online. Association for Computational Linguistics.
- Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. [Exploring the limits of transfer learning with a unified text-to-text transformer](#). *Journal of Machine Learning Research*, 21(140):1–67.
- Ehud Reiter and Robert Dale. 2000. *Building natural language generation systems*. Cambridge university press.
- Irene Solaiman, Miles Brundage, Jack Clark, Amanda Askell, Ariel Herbert-Voss, Jeff Wu, Alec Radford, Gretchen Krueger, Jong Wook Kim, Sarah Kreps, et al. 2019. Release strategies and the social impacts of language models. *arXiv preprint arXiv:1908.09203*.
- Adaku Uchendu, Zeyu Ma, Thai Le, Rui Zhang, and Dongwon Lee. 2021. Turingbench: A benchmark environment for turing test in the age of neural text generation. *arXiv preprint arXiv:2109.13296*.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *arXiv preprint arXiv:1706.03762*.
- Sean Welleck, Ilia Kulikov, Stephen Roller, Emily Dinan, Kyunghyun Cho, and Jason Weston. 2020. [Neural text generation with unlikelihood training](#). In *International Conference on Learning Representations*.
- Thomas Wolf, Julien Chaumond, Lysandre Debut, Victor Sanh, Clement Delangue, Anthony Moi, Pierric Cistac, Morgan Funtowicz, Joe Davison, Sam Shleifer, et al. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45.
- Ze Yang, Can Xu, Wei Wu, and Zhoujun Li. 2019. Read, attend and comment: a deep architecture for automatic news comment generation. *arXiv preprint arXiv:1909.11974*.
- Rowan Zellers, Ari Holtzman, Hannah Rashkin, Yonatan Bisk, Ali Farhadi, Franziska Roesner, and Yejin Choi. 2019. Defending against neural fake news. In *Advances in Neural Information Processing Systems*, pages 9054–9065.