Generating texts under constraint through discriminator-guided MCTS

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ABSTRACT
Large pre-trained language models (LM) based on Transformers allow to generate very plausible long texts. In this paper, we explore how this generation can be further controlled to satisfy certain constraints (eg. being non-toxic, positive or negative, convey certain emotions, etc.) without fine-tuning the LM. Precisely, we formalize constrained generation as a tree exploration process guided by a discriminator according to how well the associated sequence respects the constraint. Using a discriminator to guide this generation, rather than fine-tuning the LM, in addition to be easier and cheaper to train, allows to apply the constraint more finely and dynamically. We propose several original methods to search this generation tree, notably the Monte Carlo Tree Search (MCTS) which provides theoretical guarantees on the search efficiency, but also simpler methods based on re-ranking a pool of diverse sequences using the discriminator scores. We evaluate these methods on two types of constraints and languages: review polarity and emotion control in French and English. We show that MCTS achieves state-of-the-art results in constrained generation, without having to tune the language model, in both tasks and languages. We also demonstrate that our other proposed methods based on re-ranking can be really effective when diversity among the generated propositions is encouraged.

KEYWORDS
nlp, constrained text generation, monte carlo tree search, discriminator

1 INTRODUCTION
Generative language models exist for a long time, but with advent of the transformer architecture [26] and increasing computing capabilities, they are now able to generate well written and long texts. In particular, large models, such as the well known GPT-2 [20] and GPT-3 [2], have been used successfully for various applications: assisting writers, summarizing, augmentating data for subsequent NLP tasks, generating fake news [15, 18, 27].

Yet, beside the prompt used to initiate the generation process, there are few options to have control on the generation process. Being able to add some constraints on the generated texts is useful for various situations. For example, it allows to create texts that follow a certain writing style, convey a certain emotion or polarity. More critically, it can be used to prevent the inherent toxicity of language models trained on the internet, or to not reproduce gender or race stereotypes.

So far, the best performing methods necessitate to fine-tune the LM, so that it specifically learns to model this constraint, i.e. the constraint is hopefully incorporated in the LM. This fine-tuning approach has several drawbacks. It implies to train multiple specific LMs, which is costly, when even possible given the size of current state-of-the-art LM.

In this paper, we propose new approaches to add such additional constraints on the texts but at generation time. We exploit a discriminator that is trained to determine if a text follows a given constraint or not; its output provides information to guide the generation toward texts that satisfy this expected constraint. In order to make the most of the discriminator information, we propose an original method based on the Monte Carlo Tree Search (MCTS) algorithm [5], namely Plug and Play Language - Monte Carlo Tree Search (PPL-MCTS). We also propose simpler methods based on re-ranking to fulfill this goal. Both approaches do not require to fine-tune the LM; adding a new constraint can thus simply be done by providing a discriminator verifying if a text comply with what is expected. More precisely, our main contributions are the following ones:

1. we propose to use MCTS to implement constrained generation and we show, on three datasets and two languages, that it yields state-of-the-art results while offering more flexibility;
2. we also explore simpler generation methods based on re-ranking and show that this kind of approach, with low computational costs, can also be competitive if the diversity within propositions to re-rank is encouraged;
3. we provide a fully functional code implementing a batched textual MCTS working with the popular HuggingFace library.

The paper is organized as follows: in the next section, we present some background knowledge about language modeling and, in Section 3, we present the few existing related work on constrained generation. In Section 4, we present ‘PPL-MCTS’, and detail how MCTS can be applied to constrained generation formalized as tree exploration. Our other re-ranking-based methods, the experimental protocol and the obtained results are detailed in Section 5. We finally present some future research avenues, and some ethics considerations in the two last sections.

2 BACKGROUND
Text generation. Language modeling estimates the probability distribution of sequences of symbols $x_1, x_2, \cdots, x_T$ (most often tokens) taken from a vocabulary $V$, with variable lengths $T$. Most commonly, the probability of one sample $x$ (also called likelihood) is defined as the joint probabilities over each of its tokens, which can be factorized using the chain rule: $p(x_{1:T}) = \prod_{t=1}^{T} p(x_t \mid x_{1:t-1})$. 

$\mathrm{x}$
Given a training set of texts, a LM can be trained by optimizing weights \( \theta \) of a neural network which outputs a probability distribution over the dictionary for the next token given the input ones, i.e \( p_{\theta}(x_t \mid x_{1:t-1}) \) at a given time step \( t \). This allows to create an auto-regressive LM that can generate sequences by iteratively using those distributions to emit a token \( x_t \), and append it to the context \( x_{1:t-1} \) for the next iteration. The generation process – or decoding – is often started using a small initial sequence: the prompt.

Decoding methods. However, how to choose a token \( x_t \) so that the final sequence has the highest possible likelihood is still an open problem. This is mainly due to the size of the search space, since for a sequence of length \( T \) and a vocabulary of size \( |V| \) (often being tens of thousand), the space has a size of \( |V|^T \), making an exact search intractable. Several search methods have been proposed to alleviate this issue; a naive one is the greedy search where the most probable token is picked at each step. A neural LM predicting logits \( z_{1:|V|} \) over the vocabulary, the probability of sampling the \( j \)th token at time step \( t \) is computed by applying softmax, usually with temperature \( \tau \) (a high \( \tau \) flattens the distribution):

\[
p_{\theta}(x_t \mid x_{1:t-1}) = \frac{\exp(z_t/\tau)}{\sum_j \exp(z_j/\tau)}
\]  

(1)

In order not to miss a more probable sequence which starts with a token having a lower probability, beam search [7] explores the \( k \) most probable sequences at each generation step. It should be noted that these search methods are highly biased towards samples that have a high likelihood in the beginning, which does not guarantee to find the sequence with the highest possible likelihood. Moreover, they tend to generate redundant texts; thus, top-k sampling [9] samples the next token from the \( k \) most probable next tokens to introduce variance. However, \( k \) is fixed and the \( k \)th token may have a very low probability (and therefore be off-topic). To improve upon this method, nucleus sampling [11] (or top-p sampling) is used to sample from the smallest set of tokens that have a cumulative probability higher than \( p \). Finally, beam sampling [3] consists in a mix of beam search and sampling. \( k \) tokens are first sampled using the LM distribution and, for each one, \( k \) more tokens are then sampled, leading to \( k^2 \) beams in which only the \( k \) most probable are kept. This process is repeated until each beam is finished.

Tuning a constrained LM. As the LM only models \( p_{\theta}(x) \), adding a constraint to guide the generation is not straightforward. The simplest way of applying a constraint to generations is to directly train a specific model \( \theta_c \) on texts that belong to a class \( c \) satisfying the constraint, thus modeling \( p_{\theta_c}(x) \). However, this approach leads to train one specific LM for each constraint, resulting in several models. The idea of constrained textual generation as we aim in this paper is rather to model \( p_{\theta}(x \mid c) \) with only one LM; hence, training is done once and the same \( \theta \) is used for every constraint.

Discriminator-guided generation. To avoid the computational cost of fine-tuning large LMs, some methods aim at controlling the generation only at decoding time. The general idea of discriminator-guided generation is to combine a discriminator \( D \) with a generative LM. Contrasting with the implicit application of constraint in tuned-models, the discriminator \( D \) explicitly models the constraint by calculating the probability \( p_D(c \mid x) \) of the sequence \( x \) to satisfy the constraint \( c \). This probability is directly related to \( p(x \mid c) \) through Bayes’ rule: \( p(x \mid c) \propto p_D(c \mid x)p_{\theta}(x) \).

With this definition, finding the sequence that maximizes \( p(x \mid c) \), consists in finding a sequence that is both well written (high LM likelihood) and that satisfies the constraint (high classification probability). Yet, as previously mentioned, finding the sequence with the highest likelihood is not simple. Adding the constraint makes the process even more complicated since the most probable sequences might not satisfy the constraint, making heuristics used in traditional search methods even worse. Even if the discriminator is trained with inputs of variable lengths, its output probabilities become necessarily more meaningful as the sequence grows and might only be trustable to guide the search when the sequence is (nearly) finished, leading to similar problems as with likelihood. Thus, to achieve good constrained generation, one needs to find efficient ways of exploring this huge search space.

3 RELATED WORK

Few methods address the constrained textual generation. Class-conditional language models (CC-LMs), as the Conditional Transformer Language (CTRL) model [13], train or fine-tune a single model directly for controllable generation, by appending a control code \( cc \) in the beginning of a training sequence. \( cc \) indicates the constraint to verify, and is generally related to a class \( c \) and a corresponding dataset. Trained with different control codes, the model learns \( p_{\theta}(x \mid c) = \prod_{t=1}^{T} p_{\theta}(x_t \mid x_{1:t}, cc) \). The constraint can then be applied during generation by appending the corresponding control code to the prompt.

While this method gives some kind of control over the generation, the control codes need to be defined upfront and the LM still needs to be trained specifically for each set of \( cc \). This is a problem since the current trend in text generation is the use of large pre-trained model which can hardly be fine-tuned (for instance, the last version of GPT, GPT-3, cannot be fine-tuned without access to very large hardware resources).

Discriminator-based methods alleviate this training cost problem, as discriminators are easier to train than a LM, and any additional constraint can be defined posteriori without tuning the LM, only by training another discriminator. The discriminators have been used in different ways to explore the search space. In the work of Holtzman et al. [12], Scialom et al. [23], the space is first searched using beam search to generate a pool of proposals with a high likelihood, and then the discriminator is used to re-rank them. However, in addition that this search can still miss sequences with high likelihood, it is biased towards the likelihood, while the best sequence might only have an average likelihood, but satisfies the constraint perfectly.

Hence, it might be more suitable to take the discriminator probability into account during decoding rather than after generating a whole sequence. In this case, the discriminator is used at each generation step to get the probability \( p_D(c \mid x_{1:T}) \) for each token of the vocabulary, and merge it to the likelihood \( p_{\theta}(x_{1:T}) \) to choose which token to emit. In order to reduce the cost of using a discriminator, GeDi [14] proposes to use CC-LMs as generative discriminators. The probability of a sequence being from class \( c \) at a given timestep...
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In the case of constrained generation, the goal is thus to find the path, and therefore the sequence x, with the highest \( p(x \mid c) \) possible without exploring the whole tree in width and depth. As mentioned previously, this probability can be computed as the product of the likelihood \( p_\theta(x) \) and the probability given by a discriminator \( p_D(c \mid x) \). An illustration of such a tree can be found in Fig. 1, where the likelihood of \( x \) is forged by multiplying corresponding conditional probabilities along the path, and the classification probability is calculated at the terminal node.

**MCTS algorithm.** MCTS is a heuristic based iterative algorithm that uses randomness to solve deterministic problems that cannot be solved using traditional approaches, often because the search space is too large to be entirely explored. Each iteration consists in four consecutive steps:

1. **Selection** Recursively choose children from the root to a node that has not been expanded yet. The children chosen are those maximizing the UCT, a formula derived from the Upper Confidence Bound (UCB) applied to Tree:

   \[
   \text{UCT} = \frac{s_i}{n_i} + c_{\text{puct}} \sqrt{\frac{\ln N_i}{n_i}}
   \]

   with \( s_i \) the aggregate score of the node \( i \), \( n_i \) the number of simulations played after this node, \( N_i \) the number of simulations played after its parent, and \( c_{\text{puct}} \) a constant defining the compromise between exploration and exploitation.

2. **Expansion** If the selected node is not terminal, expand it by creating its children.

3. **Simulation (roll-out)** Choose one of these children randomly, and go to a terminal node through a random walk or another pattern.

4. **Backpropagation** Aggregate the final score obtained at the terminal node to each parent until root. There are different strategies to aggregate scores, for example, compute the average between the actual score and the one being back-propagated, or take the maximum of the two.

Applying MCTS to text generation. In the particular context of applying MCTS to text generation, expansion and simulation steps are driven by the LM. Some adaptations can be made. For example, to only explore viable sequences, logits of the LM can be used during the selection phase. To this end, the Polynomial Upper Confidence Trees (PUCT) [21, 25] serves as the selection formula:

\[
\text{PUCT}(i) = \frac{s_i}{n_i} + c_{\text{puct}} p_\theta(x_i \mid x_{1:t-1}) \frac{\sqrt{N_i}}{1 + n_i}
\]

where \( p_\theta(x_i \mid x_{1:t-1}) \) is the probability of token \( x_i \) given by the LM defined in (1).

In the task of constrained generation, we define the score of a sequence as its probability knowing the class \( p(x \mid c) \). The aggregated score \( s_i \) associated to the node \( i \) is the averaged probability over all simulations played after the node.

When the number of iterations has reached the allocated budget, the building of the tree stops. The token \( x_i \) selected for the current decoding step can be selected as the most played node amongst the root’s children nodes, or the one with the highest aggregated score. We chose to select the most played one.

\[ i \text{ is then given by:} \]

\[
p_\theta(c \mid x_{1:t}) = \frac{p(c)}{\sum_{c' \in C} \prod_{j=1}^{t} p_\theta(x_j \mid x_{1:t-1}, c')}
\]

where \( C \) is the set of classes. The method relies on the fact that during sequence generation, the CC-LM computes \( p_\theta(x_t \mid x_{1:t-1}, c) \) at each time step for all tokens of the vocabulary, so that most terms of (2) are already computed during online generation (all \( j < t \)). This approach is thus at the intersection of tuning the LM and using a discriminator: it tunes a small LM (the CC-LM) to guide a bigger one.

In Plug And Play Language Model (PPLM) [6], the discriminator is used to shift the hidden states of the pre-trained transformer-based LM towards the desired class at every generation step. PPLM can be used on any LM and with any discriminator. However, PPLM needs to access the LM to modify its hidden states, while the approach we propose only requires the output logits. As some new LM can only be used through access to logits (e.g. GPT-3 API), this makes PPL-MCTS more plug and play than PPLM.

A common drawback of all these approaches is their lack of a long-term vision of the generation. Indeed, since the discriminator guides the generation, classification errors will cause the generation process to deviate further and further. However, the meaning of a word can often only be defined once the context is fully known. Trying to optimize a score defined in the long horizon by making short term decisions is very similar to common game setups such as chess, where the Monte Carlo Tree Search (MCTS) has proven to be really effective [24], which motivated our approach.

### 4 PPL-MCTS METHOD

The approach we propose is in line with methods using a discriminator to guide a large LM model, without the need to re-train it. Unlike previous approaches, it is able to have a long term vision on what is generated. Being able to make a short-term decision (choice of the next token \( x_t \) at time step \( t \)) that is promising in the long run is based on the exploration of the search space. We propose here to use the Monte Carlo Tree Search (MCTS) for an efficient exploration of this space.

MCTS is very well suited for this problem for three reasons. First, it allows to get a local score (i.e., a score for the next token to emit) using finished sequences. Hence, this score is more meaningful than scores based only on the next step. Second, it allows to explicitly define the compromise between exploitation of promising sequences (with an high likelihood), and exploration of other potentially promising sequences (to not miss better sequences with a lower likelihood). The fact that regret, i.e the number of simulations done on a sub-optimal sequence, has a theoretical upper bound in MCTS is a nice guarantee that the computation time is not wasted and the search is efficient. Finally, it outputs a solution at each iteration and so can fit our computational budget by allowing to adjust the quality of the solution to calculation spent.

Text generation as tree exploration process. The search space of the text generation corresponds to a tree: its root is the prompt and the child of a node is its father’s sequence with one of the \( |V| \) possible token appended.
These adaptations of MCTS to constrained generation define our proposed approach: Plug and Play Language - Monte Carlo Tree Search (PPL-MCTS), summarized in Fig. 2. MCTS has been used in recent work [17] for machine translation, where the authors try to optimize the metric used for evaluation in machine translation: BLEU and BERTScore. Indeed, the final score can be defined to guide the decoding in order to optimize a particular aspect of the generated sequence. Our work mainly differs in the target goal and the way the score is defined. Rather than directly optimizing a target metric, we use MCTS to find the sequence with the highest \( p(x | c) \) possible using a discriminator \( D \) to score how well the desired constraint is satisfied.

**Model improvements.** In order to allow a finer control on how the constraint is applied, we introduce a parameter \( \alpha \in [0, 1] \) to control the compromise between likelihood and constraint strength, modifying Bayes’ equation:

\[
p(x | c) \propto p_D(c | x)^{\alpha} p_\theta(x)^{1-\alpha}
\]  

(5)

Note that PUCT already considers the likelihood of the sequence, favoring the selection of nodes with high likelihoods. Setting \( \alpha < 1 \) forces the algorithm to explore solutions even closer to the language model. In our experiments, we set \( \alpha = 1 \) to strengthen the classification constraint.

To avoid expensive roll-outs, one may also assign a value to unfinished sequences at the cost of a less precise evaluation that may be not as meaningful as when doing roll-outs. Indeed, the discriminator can be trained on sequences with variable numbers of tokens, allowing it to be used at each node without the need of simulations. In this setup, the MCTS is used as an efficient compromise between exploration and exploitation, losing part of its long view property but allowing to skew the exploration toward promising solutions.

Finally, during our first experiments, we observed that PPL-MCTS leads to repetitive patterns. This is very similar to what happens with greedy search, where a single sequence with an high likelihood is dominating the search. If such sequences also have a pretty high discriminator scores, they will be repeated often. CTRL [13] offers a simple yet very powerful method to avoid noisy repetitions, while allowing to output a sequence that has already been produced. It applies a scalar factor \( I(i) \) to the temperature parameter of a given token \( x_i \) that penalizes this token if it is already in the input sequence. Hence, the probability of a given token becomes:

\[
p_\theta'(x_i | x_{1:t-1}) = \frac{\exp(z_i / (\tau \cdot I(i)))}{\sum_o \exp(z_o / (\tau \cdot I(o)))}
\]  

(6)

with \( I(i) > 1 \) if \( x_i \) is already in the prompt and 1 otherwise. Thus, probabilities of already emitted tokens are penalized but if the language model gives a really high score to one token (hence, it is very confident that this is the token to emit), it may still be selected as the output token.

### 5 EXPERIMENTS

#### 5.1 Performance assessment

The goal of constrained generation is to generate samples that 1) belong to a specific class while 2) keeping the language quality of the original LM and 3) with enough diversity across generations. We chose three different metrics to evaluate each of these aspects: 1) accuracy, which is automatically verified by an external “oracle” discriminator trained on a dataset disjoint from the one used to guide the generation; 2) perplexity, which is computed by using an “oracle” LM, i.e., an unconstrained LM trained on different data than the one used to train the constrained generator; 3) Self-BLEU score [29], which is the BLEU score [19] of a sample using the other samples as references (high Self-BLEU score means that there is a lot of overlap between generated samples and thus that the diversity is low). Such automatic metrics have known limitations [3] but allow to get an overview of achievable performance.

In practice, the studied dataset (see below) is split into two parts, each part being sub-divided in train/val/test sets. The first part...
serves to train models used for the generation (LM and discriminator), while the second is used to train oracles which serve to compute the evaluation metrics. The test set of this second part will also be used to forge prompts for the generation. Each metric is evaluated on a pool of 900 generated samples.

5.2 Datasets

Three different datasets are used in the experiments presented hereafter: amazon_polarity [28], CLS (from the FLUE [16] dataset) and emotion [22]. They are available at https://huggingface.co/datasets/. The first two are Amazon reviews which have been labeled as positive or negative, so the intended task is to study the possibility of applying polarity to the generation. These two datasets have been chosen even if they are really similar because CLS is in French and will serve to ensure that these methods can work on other language than English. Emotion is a collection of tweets that have been classified under eight basic emotions: anger, anticipation, disgust, fear, joy, sadness, surprise and trust. This dataset is supposed to be more challenging since there are more classes and texts are smaller (only composed of one sentence), hence the model needs to precisely generate the good emotion with few tokens.

It is worth noting that the 3 datasets have different sizes: 4,000,000 instances in total for amazon_polarity, 20,000 for emotion and 6,000 for CLS. Since generally speaking, training a discriminator is easier than training a LM, this difference allows to study what is the impact of the size of the training data on the generative approaches and more precisely, if discriminator-based approaches are more efficient than those based on tuning LM when there is less data.

We adapted prompts used to start the generation for each dataset depending on the data format. Amazon_polarity comes with a “title” column which corresponds to the title the user gave to the review. This field is directly used as prompt since it is particularly well suited. The two other datasets only have one text field, hence the corresponding prompt is the very first tokens of this field. Because texts of emotion and CLS have different lengths, the size of the text used as prompt is also different: they are arbitrarily set to 6 tokens for CLS and 4 for emotion.

5.3 Methods and baselines

Different approaches of constrained generations are evaluated on each dataset.

5.3.1 Baselines. Beside PPL-MCTS, we propose several baselines and simple techniques. First, re-ranking is explored with different variations, in the way sequences to re-rank are produced, and in the way the final sequence is chosen. Indeed, most studies create propositions to re-rank using beam search and then re-rank using the product of likelihood and discriminator probability. As suggested in [17], re-ranking is competitive but needs more exploration, notably on the diversity aspect. Thus, we propose diverse original methods to study performances achievable with this basic approach. Three methods are tested to generate propositions: beam search (with a beam size of 3), nucleus (top-p) sampling (with p=0.9), as well as beam sampling. For the final choice, we also propose three different methods : argmax, where the sequence that has the highest \( p(x|c) \) is chosen, first true, where propositions are sorted by descending likelihood and the first sequence that belongs to the correct class according to the guiding discriminator is chosen, and sampling, where the distribution of \( p(x|c) \) for the propositions is normalized and the chosen sequence is sampled following this distribution. Similarly to PPL-MCTS, the likelihood part of \( p(x|c) \) is omitted (i.e., \( \alpha = 1 \)) since sequences in the pool of propositions already have a relatively high likelihood.

It should be noted that in our setting, a generated sequence corresponds to a document (e.g., a whole review). This choice makes sense for our datasets, but re-ranking at a smaller level (after each sentence, after \( x \) tokens...) would also be possible and might produce different results.

5.3.2 Methods from the literature. We compare our results with methods from the literature. In particular, we test CC-LMs trained on the target task, similarly as CTRL. We tested this method using greedy search as well as sampling for decoding. We also propose an implementation of CC-LM trained with the classification loss initially proposed for the GeDi method [14]. These CC-LMs are further used to implement the state-of-the-art GeDi model. In the experiments reported below, we report results for GeDi models trained with and without the classification loss. Finally, we report results of PPLM. For a fair comparison, the same discriminator and LM are used for our PPL-MCTS approach, the re-ranking approaches (baselines), and PPLM.

5.4 Experimental setting

For each method, a number of tokens equals to the average length of sequences of the dataset are generated: 98 tokens for amazon_polarity, 23 for emotion and 137 for CLS. Fixing the number of generated tokens allows to make the fair comparisons with the tested methods since the perplexity of a sequence is directly linked to its length, and its number of n-gram impacts the Self-BLEU metric. An example of generation is given in Fig. 3.

To run all of these methods, three different models are needed: one discriminator, a “vanilla” LM used as generator, and the CC-LMs used in the CTRL and GeDi approaches. For the discriminator used to guide the generation, we rely on BERT-base-cased [8] for the English datasets and FlauBERT-large-cased [16] for CLS. As vanilla LM, we use GPT-2 small models, relying on OpenAI’s pre-trained model for the English datasets and on belgpt2 for the French one. The implementation and models used for BERT, FlauBERT, GPT-2 and belgpt2 are all found on https://huggingface.co/. The CC-LMs are simply fine-tuned versions of the vanilla LM with the control code appended. Given the particular format of data on our experimental datasets, the vanilla LM is trained on raw training.
sequences in order to produce texts corresponding to the task (for instance, reviews).

We tested three values for the temperature parameter for each proposed method (1.0, 1.1 and 1.2) and we only report the results for the one yielding the best accuracy score. For PPL-MCTS, we also studied the impact of $c_{pact}$ by testing values 1.0, 3.0, 5.0 and 8.0 along with the different temperature values mentioned. The repetition penalty has been set to 1.2 as defined in CTRL. The number of MCTS iterations per token is set to 50, as well as the number of propositions for re-ranking, except for beam sampling where it is set to 10 because of memory limitations. Given the cost of roll-out for long sequences, we apply roll-out only on the emotion dataset to be able to run extensive experiments. Without roll-out, MCTS looses a part of its long view property but still allows to skew the exploration toward promising solutions. A study of the impact of the roll-out is detailed in a next sub-section. Parameters used for literature models are those provided by the authors. Experiments were conducted on a Quadro RTX 6000 with 80 Go of RAM.

5.5 Results

Results on the emotion, CLS and amazon_polarity datasets are respectively reported in Tables 1, 2 and 3. The statistical significance against GeDi and PPLM is measured applying a t-test with significance level (p-value) of 1%. Results show that PPL-MCTS is competitive against task-specifically trained LMs on the constraint application aspect (high accuracy) while keeping a fair amount of diversity (low Self-BLEU) and staying close to the original distribution (low oracle perplexity). On all three datasets and metrics, it constantly yields top results; the only other method which is high-performing for all metrics and constant across the datasets is GeDi trained with the classification loss.

Another remarkable result is for the sampling - argmax method that selects the proposition that has the higher probability to be from the correct class among a pool generated using sampling. Thanks to the sampling used for generating propositions, its Self-BLEU is among the lowest of all reported values. Despite the simplicity and low computational cost of this approach, its accuracy is among the best on every dataset. These very good results should however be put into perspective of the very high perplexity of its generated texts. It indicates that the generated samples may be very different than those generated by a standard LM on this dataset. Hence, exploring accuracy/perplexity compromises, achievable with different values of $\alpha$, would be interesting.

5.6 Effect of the roll-out

Rolling out is costly for very long sequences, and the question of its usefulness necessarily arises. We study how rolling out for only a fixed number of tokens (instead of until the end of the sequence) influences the performance of PPL-MCTS. For this experiment, we use the CLS dataset and set the roll-out to 0 (original result), 3, 5, 10 and 20 tokens. As one can note in Fig. 4, only 5 tokens allows PPL-MCTS to be on par with GeDi on this dataset. The roll-out size quickly improves accuracy, which then reaches a plateau. It suggests that having an horizon is really helpful but only to up to a given point. Conversely, Self-BLEU and oracle perplexity values stay stable, varying respectively from 0.54 to 0.57, and from 4.98 to 5.18 as the roll-out size increases from 0 to 20.

Finally, it should be noted that for a relatively small – fixed number of tokens, the cost of the roll-out is marginal compared to the global cost of PPL-MCTS.

6 CONCLUSION

In this paper, we show that it is possible to control generation with the help of a discriminator that implements some expected constraint on the text. This makes it possible to use a pre-trained LM, without further training. This flexible approach is very useful.
when using very large models such as recent GPT-3 for which the computational cost for the fine-tuning is prohibitive. In contrast, training a discriminator is easier and cheaper than tuning a LM. The methods that we propose to mix the discriminator constraint and the generation yield performance that is equivalent to the best approaches based on LM tuning. On the other hand, such approaches are more expensive during inference, because of the additional cost of the discriminator and a more complex decoding process. GeDi tackles this extra cost by using CC-LM as discriminator. Seeing text generation as a tree exploration process, it lowers the cost of width exploration but the depth exploration is still an issue, since it is now very similar to a standard maximum likelihood search. Monte Carlo Tree Search provides an efficient way to determine the best local choice in the long run, lowering the cost of depth exploration. Thus, these two methods solve different facets of constrained generation, and the combination of the two is a promising perspective.

Moreover, MCTS allows to precisely define the best compromise between cost and quality, while ensuring the efficiency of the search theoretically. For reproducibility purposes, our implementation is made available at https:ANONYMOUS-URL

Several research avenues are opened by this work. For methods yielding high perplexity, we will try to reach a better compromise between accuracy and perplexity by tuning the parameter $\alpha$. Similarly, the size (number of tokens considered) of the roll-out in MCTS offers some ways to control the cost/performance compromise. Having an adaptive roll-out size, as in [4], would seem particularly suited for texts. Last, it should be noted that fine-tuning a model and controlling the generation with a discriminator can be used conjointly. For instance, one can use MCTS on a tuned LM, which will most likely result in even better results because sequences considered during the search will have an overall higher quality for the considered task.

7 ETHICS/BROADER IMPACT

The ethical risks of large LMs are well known [1]. Especially when they are trained on large quantities of non curated data, it has been shown that they tend to reproduce or amplifies biases on gender, race, etc. and more generally may produce inappropriate content [10]. Constrained generation as we propose is one way to control, a posteriori of the LM training, that the generated texts respect some criteria. The ethical interests are thus important, such as adding constraint about race diversity, gender equality, non toxicity, etc. But of course the same technique could be used for malicious purposes, such as constraining generation so it produces offensive texts, targeted fake news, etc.

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Table 3: Performances of constrained generation methods; amazon_polarity dataset. † (resp. ‡) indicates statistically significant improvement against GeDi-classloss (resp. PPLM).

| Generation method | Accuracy ↑ | 5 - Self-BLEU ↓ | Oracle perplexity ↓ |
|-------------------|------------|----------------|--------------------|
| Tuned LM          |            |                |                    |
| CC-LM - Classloss | 0.82       | 0.79           | 2.56†              |
| CC-LM             | 0.91       | 0.71           | 3.21‡              |
| GeDi - Classloss  | 0.96†      | 0.6†           | 5.16               |
| GeDi              | 0.96†      | 0.6†           | 5.16               |
| Untuned LM        |            |                |                    |
| PPLM              | 0.89       | 0.66           | 2.84†              |
| Beam - Argmax     | 0.88       | 0.85           | 3.14‡              |
| Beam - Sampling   | 0.86       | 0.84           | 3.27†              |
| Beam - First true | 0.85       | 0.83           | 3.27†              |
| Beam sampling - Argmax | 0.97† | 0.73       | 3.82‡              |
| Beam sampling - Sampling | 0.92   | 0.76       | 3.68‡              |
| Beam sampling - First true | 0.90   | 0.73       | 3.84‡              |
| Sampling - Argmax | 0.99††     | 0.17††        | 16.5               |
| Sampling - First true | 0.89     | 0.07††        | 85.9               |
| Sampling - Sampling | 0.88     | 0.17††        | 16.3               |
| PPL-MCTS          | 0.97†      | 0.63†         | 5.69               |

Figure 4: Accuracy (%) according to the roll-out size; CLS dataset
8  PPL-MCTS: TECHNICAL APPENDIX

We provide in this technical appendix additional information on the experiments. Further experimental results, as well as examples, are given and discussed.

8.1 Data splits

We adapted the way we split the dataset into two parts and train/test/validation sets depending on the original datasets splits. Amazon_polarity is composed of a training set of 3 600 000 examples and a test set of 400 000. We split both in two and kept 20% of each training set for validation. Emotion already comes with train, test and validation set, hence we just split each in two. Finally, CLS is composed of a train and test sets that have a size of 6000. We split the training set in two and split the test set twice so we got two validations and test sets.

The first train and validation sets are used to train and control the training of models used for the generation: the guiding classifier, “vanilla” LM and CC-LM. The test set serves to verify their performance.

The second ones are used to train the LM oracle and the classifier used to measure the accuracy. The test set allows to verify that these models are trustable for accurate evaluation. Once all the models are trained, the controlled generation is evaluated on 900 samples generated from prompts never seen by the discriminator.

8.2 Complementary results

We tested three values for the temperature parameter for each proposed method: 1.0, 1.1 and 1.2. As the temperature grows, the output distribution of the language model becomes more and more uniform. This mean that high temperatures should result in high perplexities because the sampling deviates further from the original distribution.

For PPL-MCTS, we also studied the impact of \( c_{puct} \) by testing values 1.0, 3.0, 5.0 and 8.0 along with the different temperature values mentioned. \( c_{puct} \) defines the compromise between exploiting nodes that already have great scores and exploring less played but promising ones. A high \( c_{puct} \) encourages exploration. We remind that the repetition penalty \( f \) in (6) has been set to 1.2 as defined in CTRL.

In Section 'Results', we reported only one set of parameter values for each method and dataset, the one that yields the best accuracy result. We report hereafter results with every tested set of parameters in Table 4, 5 and 6 for respectively the emotion, CLS and amazon_polarity datasets.

Unsurprisingly, the perplexity of methods which sample on the LM logits explodes when \( r \) grows, without a noticeable gain in accuracy. Since the diversity is already high for low \( r \) values, it seems to be better to keep the temperature low with these approaches. Note that the couple \( c_{puct} = 3 \), \( r = 1.0 \) for PPL-MCTS always leads to the best result for this method. Using \( c_{puct} = 8 \) seems to yield slightly worse results, especially with a low temperature. However, the different parameters do not greatly affect the results of PPL-MCTS.

8.3 Examples of generation

We provide an example of generation for amazon_polarity and emotion datasets using PPL-MCTS, PPLM, GeDi and Sampling -
I enjoyed this book. It was realistic and I enjoyed the way the author described the people and places. I would recommend this book to anyone who is going to be much... this movie has a lot of realism to it too! and i was totally impressed on how good the kids and

Table 5: Results for every tested set of parameters on the proposed methods; CLS dataset. Results reported in the body of the paper are in italic.

Table 6: Results for every tested set of parameters on the proposed methods; amazon_polarity dataset. Results reported in the body of the paper are in italic.

PPL-MCTS

PPLM

GeDi

Sampling - Argmax

Figure 5: Example of constrained generations using PPL-MCTS, PPLM, GeDi and Sampling - Argmax methods (from top to bottom) on the 'love' class, using the same prompt (in bold) from emotion.

Figure 6: Example of constrained generations using PPL-MCTS, PPLM, GeDi and Sampling - Argmax methods (from top to bottom) on the 'love' class, using the same prompt (in bold) from emotion.