Controllable and contextualised writing tool for novel authors

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Abstract

Complex language models trained on huge text corpora have shown unparalleled text generation capabilities, and thanks to transfer learning, are accessible to a greater number. However, despite recent developments, users are not yet able to fully control particular aspects of the text produced. This is why we propose a finetuned OpenAI GPT-2 model for controllable and contextualised text generation specific to novels. By integrating it into a web-service, we would like to enable authors to write and ask for automatic text generation which is consistent with both previous and next paragraphs. They can specify the genre of their book, the length of the desired text, the entities it should mention and its content via keywords or a short summary. We explore the technical possibilities and limitations around these objectives.

1 Introduction

1.1 Motivation

The Transformer architecture (Vaswani et al., 2017) has enabled large scale language models trained on huge text corpora (Devlin et al., 2018; Dai et al., 2019) to improve significantly the state-of-the-art natural language processing. Regarding the specific task of text generation, OpenAI GPT-2 (Radford et al., 2019) has reached outstanding performance and produces something close to what humans would write. However, it suffers from one major drawback: its output is not controllable. Steering generation thus has been the focus of some recent papers (Hu et al., 2017; Logeswaran et al., 2018). Among the most successful, CTRL (Keskar et al., 2019) and PPLM (Dathathri et al., 2019) introduced respectively control codes and an attribute model to help govern style, theme and task specific behaviour. Others, like Grover (Zellers et al., 2019), create fake news article using information about author, domain, data and headline.

These papers pave the way of future controllable text generation and demonstrate great possibilities. However, they show some limits; only a few definite features are controllable at once and user interaction remains restricted. Furthermore, despite being more accessible thanks to transfer learning, the lack of open source platforms and the difficulty to maintain a consistent context across long paragraphs have limited their spread towards day-to-day applications.

Being aware of such limitations, we join the recent trend of research papers that try to overcome these shortcomings. In particular, we wish to fill in a gap in the literature by building a tool aimed at helping an author write a novel. Our work can be decomposed into two steps. The main one being to find an original approach leading to a controllable and contextualised text generation, specific to novels. The second one being to integrate it into an interactive open-source web-service that allows any author to benefit from it. The code is available at https://github.com/WeazelDev/AITextGenerator and the front-end at http://textgen.thomas-lamson.com/.

Our objective is to make users, at any point when writing a novel, able to automatically generate new sections that are consistent with the rest of the writing, especially previous and following paragraphs. We leave them the opportunity to select entities (characters, locations, etc.) that they have introduced in their novel and that they want to include in the new section. Similarly, they can specify the size of desired text, its content via a small summary or keywords and even the genre of the book they are writing. In the end, the tool we propose automatically makes several suggestions that users can choose from and edit. The objective being to produce creative outputs that give ideas to the writers while respecting the following constraints:

- Ensure fluency and a correct syntax.
- Consistently fill in the gap indicated by the author while conforming with surrounding context.
- Respect the desired length and genre.
- Use the selected entities and reflect the summary of the desired content.
1.2 Technical solution

One issue here, as evoked in some papers, is the computational resources needed to train these big models (Shoeybi et al., 2019; Keskar et al., 2019). Grover (Zellers et al., 2019) for instance, with its 1.5 billion parameters, required a training time of two weeks with 256 TPUs, which costed 35k $. Due to our limited financial and computational resources, we were not able to train from scratch a powerful model that produces believable sentences. We were also unable to handle tremendous models endowed with billions of parameters, such as GPT-2 1.5B. (Radford et al., 2019).

In this paper, we fine-tune a GPT-2 117M model’s parameters on 313 carefully pre-processed novels. We choose this model not only because it is one of the best text generators but also because it seems possible to contextualise the generation, despite being only a decoder. The latter is well illustrated by Hugging Face’s conversational AI1 and Gwern Branwen’s GPT-2 Poetry2.

The general idea is pretty simple: usual text generation methods work by computing the probability distribution of the next word based on previous words (Siddharthan, 2002; Bengio et al., 2003):

\[ P(w_t|w_1, w_2, ..., w_{t-1}) \]

What we want to do is to condition this probability on a structured (theme, length of text, list of entities) and unstructured (content summary, previous and following paragraphs) context that will be specified by users. This yields:

\[ P(w_t|\text{context}_{1:n}, w_{1:t-1}) \]

This way, when computing the probability distribution for token \( w_t \), GPT-2 model will have access to the context information established by users while our fine-tuning will have made it able to understand the input data format.

In summary, our key contributions are:

- Introduction of a novel GPT-2 fine-tuning approach for contextualised and controlled text generation.
- Results benchmark with original GPT-2 and examination of various metrics to quantify the effectiveness of our approach.
- Innovative User Interface (UI) ideas for a practical authored generation tool in an open-source JavaScript/Python web-service.

Finally, one of this paper’s key characteristic is the integrated use of multiple models. Although the core generation is based on OpenAI GPT-2, we employ several other models like BERT, BART, T5, etc. (see next section for references) at different steps of the project (data generation, new metrics, web-service). With this approach, we hope to inspire new cross-uses of such models in the field.

2 Related Work

Language modelling: The field of Natural Language Processing has undergone amazing progress in recent years, especially through language models (Bengio et al., 2003). One key idea at the origin of this improvement consists in embedding the meaning of a particular word into a vector of scalars of chosen dimension (Mikolov et al., 2013; Pennington et al., 2014). These word embeddings, or token embeddings, made it possible to perform a wide variety of tasks such as machine translation (Edunov et al., 2018), question-answering (Yang et al., 2019) or sentiment analysis (Radford et al., 2017) much better than existing statistics and grammar based approaches. In addition to reaching higher performances in the vast majority of tasks, it also started a new era of research. More recently, the use of the Transformer architecture (Vaswani et al., 2017) in some models like BERT (Devlin et al., 2018) revolutionised the field, improving dramatically our ability to capture the meaning of a word, a sentence or a document. Building on this, OpenAI described a transformer-decoder-only architecture focused on text generation: GPT-2 (Radford et al., 2019), which achieved outstanding performance.

Controlled text generation: Current state-of-art approaches for controlled text generation involve either training conditional generative models (Ficler and Goldberg, 2017; Keskar et al., 2019), fine-tuning existing models with Reinforcement Learning (Ziegler et al., 2019) or training generative adversarial networks (Yu et al., 2017; Zellers et al., 2019). They yield high quality results but this comes at the expense of a huge training necessitating vast computational resources. To go around this, an even more recent approach, namely PPLM (Dathathri et al., 2019), introduces a plug and play model that does not require retraining any conditional generative model. Similarly, our goal is conditional generation from a pre-trained unconditional model, avoiding big training needs. However, unlike them, we combine the large-scale pre-trained unconditional model, in this case OpenAI GPT-2, with a transfer

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1 https://github.com/huggingface/transfer-learning-conv-ai
2 https://www.gwern.net/GPT-2
learning fine-tuning technique. From this perspective, our work is similar to Hugging Face’s state-of-the-art conversational AI\(^3\) that contextualises dialog on both previous history and the bot’s ‘personality’.

**Interactive story telling:** Building on the above, some papers have chosen to explore controlled generation to assist story writing (Peng et al., 2018; Luo et al., 2019). In addition to research papers, a few open source websites like plot generator\(^4\) or talk to transformers\(^5\) generate stories where the author is sometimes asked to provide some context. It is nevertheless quite rudimentary. AI Dungeon\(^6\) is maybe the only exception and their amazing work motivated us to conduct this research. All in all, our work greatly differs from theirs in its objectives.

**Text summarization:** It is the task of producing concise and fluent summaries while preserving key information content and overall meaning. Extractive summarization methods, like Refresh (Narayan et al., 2018) or BERT SUM (Liu, 2019), which is a simple variant of BERT (Devlin et al., 2018), returns specific passages of the document that are considered important. In contrast, abstractive summarization methods, like Pointer Generator Networks (See et al., 2017) or Unified pre-trained Language Model (Dong et al., 2019), generate a new text that conveys critical information from the original text. Although human summaries are abstractive, most research has been focused on extractive summarization until recently, when seq2seq framework with bidirectional encoder and left-to-right decoders such as BART (Lewis et al., 2019) and T5 (Raffel et al., 2019), have shown promising results.

### 3 Method

Before delving into the details of the process, let’s make clear the intuition behind our approach. We train our model to re-generate each book’s paragraph (called P2) using the previous and following paragraphs (P1 and P3) as well as information concerning P2: its size, the genre of the book it belongs to, the entities it showcases and a summary of its content. As evoked, we do not train a model from scratch but fine-tune a pre-trained GPT-2 model, teaching it to predict the next word using the above contextual information and already generated words. This helps our model learn how to generate paragraphs that are consistent with the provided context. Since it is trained on many books, it will hopefully be able to generalise and satisfy the objectives mentioned in the introduction.

Our approach is thus separated into three main steps. First, we create the appropriate database. Secondly, we transform and feed the data to GPT-2. Thirdly, we fine-tune the model.

#### 3.1 Data

In this section, we emphasise some key aspects of the data generation phase since the contextualisation of the pre-trained GPT-2 strongly depends on it.

**Novels data:** Our paper focuses on text generation for novels and thus requires adequate data. We use the famous open book library Project Gutenberg\(^7\) to train our model. For each book existing on Gutenberg, we create a json file with its cleaned textual content and its related metadata: author, title, language, theme and genre. Note that a unique genre per book is manually defined from unstructured thematic information. It is the only metadata among those mentioned that we use for the fine-tuning and it is also exploited to filter the data. Indeed, we are interested and thus only keep books written in English and corresponding to a novel (using the genre tag). Although the process originally applies for all books on Gutenberg, we consider 500 of them due to limited computational resources and 313 are finally retained for training, after the filtering step. We then split the text of each book into paragraphs of different lengths, with a minimum and maximum bound, being careful not to cut a sentence in the middle, nor to separate core parts like chapters or even to split big paragraphs into uneven pieces. This step is essential as we will later learn to reconstruct them; the whole training builds on this split. Note that we store the size of each paragraph as a number of characters, which will then be used to categorise them as either Small, Medium or Large.

**Entity extraction:** Once each book is processed as detailed above, we detect entities for each paragraph using a pre-trained BERT NER Large model\(^8\). We sort them according to four categories: persons, locations, organisations and miscellaneous. Training the model with this data makes it capable of generating text that

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\(^3\)https://github.com/huggingface/transfer-learning-conv-ai
\(^4\)https://www.plot-generator.org.uk/story/
\(^5\)https://talktotransformer.com/
\(^6\)https://aidungeon.io/
\(^7\)https://www.gutenberg.org/
\(^8\)https://github.com/kamalkraj/BERT-NER
contains the established entities. It allows authors to specify the ones that they want to incorporate in the generation.

Summary: Similarly, in order for authors to be able to guide the generation by giving information on the desired content, we derive four very different summaries of each paragraph using state-of-the-art summarizers. Refer to the Related Work section for more information on text summarization. Using various summary types tends to make our model more robust to the possible ways authors could provide this type of information. Indeed, if users give the first sentence or a key sentence of the desired paragraph, extractive summarization via BertSum (Liu, 2019) will suit perfectly. On the other hand, if authors provide a detailed or brief summary of their idea, we will apply abstractive summarizers such as BART (Lewis et al., 2019) or T5 (Raffel et al., 2019), which have been fine-tuned differently to output texts of disparate lengths and employ distinct techniques. Finally, this paper incorporates a summarizer (denoted KW) that extracts keywords from the paragraph, allowing users to provide an unstructured sequence of words as a summary of the content (Mihalcea and Tarau, 2004). It builds on graph theory as it constructs a word graph of the text based on co-occurrence in a sliding window of size two. It then uses the pagerank centrality metric and POS tag to extract keywords from the word graph.

As a result, we obtain a json file per book containing the novel’s related metadata (author, title, language, genre, theme) as well as the entire text split into paragraphs. Each of them comes with four different summaries (Bart, T5, BertSum, Kw) and a list of entities that appear in it. All entities and one summary chosen at random are fed to the GPT-2 model alongside metadata information (size and genre) and pure text (P1, P2, P3) to help it control and contextualize the generation. Figure 1 illustrates this step.

3.2 Preparation step

We distinguish training mode from evaluation and generation modes. This section is dedicated to the training mode only.

We want each datapoint to have the following form:

```
[P3] P3 [Sum] Sum [T] Theme
[Ent] Entities [Size]
[P1] P1 [P2] P2 <endoftext>
```

where [P1], [P2], [P3], [Sum], [T] and [Ent] indicate the type of input received by the model (special tokens). [Size] is slightly different as it can be any of [S], [M] or [L] and gives information about the paragraph’s length. The rest simply refers to the data stored in the json files and is easily accessible. Note that the order of the input is not essential. We only put P1 at the end so that GPT-2 can continue from there, as it has been trained to do so.

Usually, during training, GPT-2 takes as input an entire text file that it tokenizes and splits into blocks of size \( block\_size \), the maximum input size of the small GPT-2 model, 1024 tokens. It then keeps them in memory in a torch dataset and loads them through a dataloader. Quite obviously, we have to proceed differently here. We do not want to feed to GPT-2 a continuous text that would be split according to its maximum input capacity but instead the blocks that we specified above, one at a time. Since they would most probably not fill in perfectly GPT-2’s input space, we pad on the right when necessary. When the input sample is too big, we truncate P1 on the left and P3 on the right, so as to stay around P2. This is not done evenly as we allocate 2/3 of the
remaining space\textsuperscript{9} to $P_1$ and $1/3$ to $P_3$, as we consider $P_1$ to be more important than $P_3$.

Once we have the framework that formats the data that we would like to pass to the model, we tokenize it using GPT-2 Byte-Pair-Encoding (BPE) Tokenizer (Sennrich et al., 2015). Note that we create special tokens for $[P_1]$, $[P_2]$, etc. This tokenized input of length $n$ has three different representations, all of shape $(1, n, 768)$ where 768 is the embedding dimension for a small GPT-2, namely:

1. **Token embeddings**: vector representations of words, learned during training.
2. **Positional embeddings**: vector representations (fixed or learned) that incorporate the sequential nature of the input, telling the model that words have a temporal property. They encode the position of a word in the input sentences.
3. **Segment embeddings**: vector representations that help the model distinguish between the different segments of the input. They mark the segment to which each token belongs to. In this case, $P_1$, $P_2$, $P_3$, theme, size, summary and entities.

The network’s input is in fact a single vector computed as the sum of the three embeddings above. We also give the network a label vector of dimension $(1, n, 768)$ that equals $−100$ everywhere except for the tokens belonging to $P_2$. This is ultimately used to compute the cross entropy loss function only between generated and original $P_2$, token by token. Indeed, we do not train the model to reproduce the full input but only $P_2$, our paragraph of interest, see Figure 2. The idea being that the model utilises the context information provided to learn a correct reconstruction of the paragraph of interest $P_2$.

### 3.3 Fine tuning

We fine-tuned the pre-trained GPT2LMHeadModel (small) from hugging face, using a customised version of their training script. GPT2LMHeadModel is a GPT-2 model transformer with a language modelling head on top of it, that is a linear layer with weights tied to the input embeddings. Its documentation is available here\textsuperscript{10} and detailed explanations about GPT-2 are accessible on the following blog\textsuperscript{11}.

We trained it on the 313 pre-processed books, using all

\textsuperscript{9}once everything except $P_1$ and $P_3$ has been fed as input

\textsuperscript{10}https://huggingface.co/transformers/model_doc/GPT-2.html

\textsuperscript{11}https://jalammar.github.io/illustrated-GPT-2/
of Hugging Face’s training settings. As mentioned, we were limited in terms of resources and could not really run this project at a larger scale. Training was performed using CUDA on an AWS’s p3.2xlarge instance (incorporating one NVidia Tesla V100 GPU) and costed about 150$. In total, the model received 134k samples for each epoch, and there were 10 epochs. However, fewer epochs might be enough to reach great performances.

4 Generation and Evaluation

4.1 Text generation framework

We now want to generate text and evaluate the performance of our fine-tuned GPT-2LMHeadModel using the transformers library from Hugging Face12. In both evaluation and generation modes, the model input is of the form:

\[
\begin{aligned}
\text{[P3]} \ & \text{P3} \ [\text{Sum}] \ \text{Sum} \ [\text{T}] \ \text{Theme} \\
\text{[Ent]} \ & \text{Entities} \ [\text{Size}] \\
\text{[P1]} \ & \text{P1} \ [\text{P2}]
\end{aligned}
\]

Unlike in training, we do not input P2. Nevertheless, we need to leave sufficient space for it to be generated since the model’s output is equal to the model’s input plus the generated sequence. Hence, the input cannot exceed a certain limit, smaller than 1024 tokens, that we determine based on confidence intervals. If the input is too big, we truncate it, similarly to what was done in training.

In this mode, after encoding the input, we generate a proper new paragraph P2 using a carefully chosen decoding strategy, embedded in the transformers generate function. More precisely, to generate a new word (or token), the model outputs a single vector and multiplies it by the learned embedding matrix. It yields an unique score for each word in the vocabulary, which determines ultimately the probability of each word to be generated. See Figure 4. Choosing the best decoding strategy and hyperparameters is a key step to obtain a good generated text, as it has a big impact on the generation. Before delving into the main decoding strategies, remember that GPT-2 is an auto-regressive language generation model so

\[
P(w_{1:T}|\text{Context}) = \prod_{t=1}^{T} P(w_t|w_{1:t-1}, \text{Context})
\]

with \(w_0 = [P2]\). The length of the generated text is determined on the fly by the <eos> token. It can however be controlled by a min_length and max_length parameter, that we use to bound the generation.

Let’s now develop the main decoding strategies.

**Greedy search:** \(w_t = \arg \max_{w} P(w_t|w_{1:t-1}).\) It is the most basic technique and consists in selecting the most probable word at each step in a greedy manner.

**Beam search** improves the greedy aspect of the model (Kulikov et al., 2019) by keeping the most likely num_beams hypotheses at each time step and eventually choosing the hypothesis that has the overall highest probability. It will always find an output sequence with higher probability than greedy search, but is not guaranteed to find the most likely output. Overall, it leads to a more fluent output but is often quite repetitive. It is particularly undesirable in story generation, even when corrected by repetition_penalty or no_repeat_ngram_size, which penalise repetitions (Yang et al., 2018; Holtzman et al., 2019).

**Top-k sampling:** sampling means randomly picking the next word according to the conditional distribution \(w_t \sim P(w_t|w_{1:t-1}).\) Lowering the temperature enables to sharpen the probability mass distribution. Increasing it fosters diversity and suits us better since we want creative outputs that give ideas to the writer, even if some mistakes are made. Top-k sampling builds on sampling, it simply selects the k most probable words and re-scales the probability mass distribution across the k selected words. This approach yields very nice results (Radford et al., 2019). Its sole limit is that k is fixed whether there is a narrow or wide distribution, while we might want to distinguish between those two cases.

**Nucleus sampling:** Instead of sampling only from the most likely k words, nucleus or top-p sampling chooses from the smallest possible set of words whose cumulative probability exceeds the probability p. The probability mass is then redistributed among this set of words. This way, the size of the set of words (a.k.a the number of words in the set) can dynamically increase and decrease according to the next word’s probability distribution. Mathematically, we want to find \(V(p)\) the smallest set of words such that \(\sum_{w \in V(p)} P(w|w_{1:t-1}) \geq p.\) This is the best approach so far (Holtzman et al., 2019) and is the one adopted by this paper, with \(p = 0.9.\)

4.2 Evaluation

We evaluate the final model, obtained after ten epochs of training, on a small portion of the training set and

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12https://huggingface.co/transformers/
on some unseen novels. To do so, for each sample considered, we generate a new paragraph $P_2$ and compare it with the true $P_2$ by computing some carefully defined metrics (see below). Analysing them helps us determine if the model yields a more contextualized and controllable generation. Only one type of summary is used at once to generate $P_2$ and consequently to assess the model. We thus perform an evaluation for each summarizer and especially focus on the two most representative ones: Keywords and BART, whose results are aggregated.

Coming back to the metrics utilised, we have implemented a few that we estimated relevant for this task, namely:

- **Perplexity** to evaluate the fluency of the model. As a reminder, it gives a measure of how probable a sentence is to the model. We expect this metric to increase slightly compared to normal GPT-2 as better contextualisation often trades off with lesser fluency. This is computed using a non-fine-tuned GPT-2 model.

- **Bert relationship** measures how the generated paragraph relates to its neighbouring paragraphs, how well it fits in. It indicates how our model deals with long contextualisation by computing the probability that $P_3$ follows generated $P_2$, normalised by the probability that $P_3$ follows true $P_2$. In practice, this metric outputs binary scores that are not very informative, so we do not include it in the results section.

- **KwCount** and **EntitiesCount** respectively output the proportion of specified entities and the proportion of keywords\(^{13}\) actually appearing in the generated paragraph. It helps evaluate the control we have over the generation.

- **BertSimilarity**, **Rouge** and **Bleu** give an indication of how close the generated $P_2$ is to the true $P_2$, meaning how well we reconstruct the initial paragraph. While Rouge uses n-grams overlap, Bleu regards precision and BertSimilarity the cosine similarity measure between their BERT [CLS] embeddings.

### 4.3 Results

To evaluate the model, we focus on the distribution of the above metrics across all paragraphs and compare our trained model with a raw GPT-2 model. Note that

\(^{13}\)they are extracted from the summary of $P_2$ if the Kw summarizer was not chosen for generation.
The overall performance of raw GPT-2 doesn’t change whether we give it the full input (P1, P3, entities, keywords...) or only a reduced input like P1 (no context), as shown by appendix Figure 10.

There are strong evidences that our model enables a greater control over the generated text. The proportion of specified entities (EntitiesCount) and keywords (KwCount) that we find in generated text is higher with our model than with GPT-2, as shown in Figure 7. This means that we are able to slightly steer the text generation according to authors’ desires, including the elements they specify more often. Similarly, appendix Figure 11 demonstrates that our model learns to adapt to the given paragraph size, without having to hard-code it in Hugging Face’s generate.

On a different note, the results demonstrated by Bert-Similarity, Rouge and Bleu (Figures 5 and 6) indicate that our model manages to reconstruct P2 better, confirming the trend perceived with the decreasing loss function (Figure 3).

Overall, our model seems to provide a more contextualised and controllable generation. The substantial improvement of all metrics compared to raw GPT-2 (with and without context information) suggests that our model learns to use the given context to generate new text, which is what we aspired to at the beginning. Nevertheless, as one could expect, this comes at the cost of a lower fluency, translated by a surge in the Perplexity metric.

Regarding human-assessed generation quality, it is difficult to truly observe it with our metrics, which is why we have made our model available to a group of authors...
and allowed them to play with it and share their results or impressions. Some generation samples can be found in the appendix. As you can notice there, generation quality is relatively poor. Although a bit disappointing, it was predictable as we are using a small GPT-2 model, whose results are far from the capabilities of GPT-2 Mega.

Finally, to grasp an idea of the evolution of the model performance, an evaluation at each epoch of the training was performed and is available in appendix Figure 9.

4.4 Further developments

An improvement we thought of consists in implementing a PPLM model on top of our fine-tuned GPT-2 model, in order to steer generation even further. We wanted to use it to control the sentiment of the text, the paragraph’s theme or the genre of the book even better. However, despite yielding great results, PPLM only allows to customise generation according to six pre-defined themes and is therefore not of great help here.

From these results, we conclude that changing the loss function might be necessary to achieve greater control. Indeed, as we keep the cross-entropy unchanged, we have no direct control on the usage of the given context and simply hope that the network will use it to better reconstruct the original paragraph. We could try to add well-designed terms to the loss. For instance, terms that penalise the absence of an entity by looking at the output vector presenting the highest similarity with the entity’s embedding. But it would require numerous iterations to be designed and tuned properly.

Finally, taking a larger GPT-2 model (Large or Mega) would definitely produce much better texts and is probably necessary if we want our web-service to be truly useful to authors. Training the model on more samples (potentially less epochs) also seems promising as it would lead to a better generalisation.

5 Open source web-service integration

During this project we also wanted to innovate and give a proposition of what an AI enhanced interface would look like in terms of user experience. We designed an interface and linked it to elastic instances in the back-end. We then opened it to a small public to test our model.

To gain in flexibility in the choice of instances to perform the heavy computations and to allow load balancing on several instances, we uncoupled the master instance - serving the javascript front-end and general data - from the computational instances - performing NER and text generation on demand. It is also possible for the client to run the servers locally to avoid delays and server overloads. Figure 8 gives an idea of the general architecture of our service.

The front-end can be accessed at the following address: http://textgen.thomas-lamson.com/. The corresponding open-source code can be found on the github page: https://github.com/WeazelDev/AITextGeneratorFront.

In this interface, users are invited to write some text in a simple editor. Named entities like characters, locations, organisations and others are detected on the fly by

![Figure 7: EntitiesCount (left) and KwCount (right). The graph shows that there is a significantly higher proportion of specified entities and keywords appearing in the generated text. However, without embedding this dimension into the loss function (penalise if omitted), we doubt that these statistics can improve much further.](image)
Figure 8: Webservice architecture

the NER backend, and are displayed on the left panel. It is made easy for users to edit them manually if needed.

Users have the possibility to select several options: length of desired paragraph, genre of their writing and list of entities they want to see appear in the generation. They can also highlight a small part of the text that will act as a summary (or a list of keywords). When they are ready, they simply need to press the Generate button and let the magic happen.

6 Conclusion

In this paper, we present an end-to-end pipeline from Project Gutenberg library’s raw text file to a web-service intended for book writers. The latter embeds a controllable and contextualised GPT-2 for text generation specific to novels. It was fine-tuned following our pipeline on a few hundreds of novels during ten epochs. Despite being limited by the computational resources at our disposal, we demonstrate that our final model is able to take into consideration the context specified by the user. With the constant improvement of computing capacities and recent research trend aimed at reducing model size without damaging generation capacities, we strongly believe such controllable generative framework will be easily accessible in the future and will greatly enhance the creativity of writers.

References

Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. 2003. A neural probabilistic language model. Journal of machine learning research, 3(Feb):1137–1155.

Zihang Dai, Zhilin Yang, Yiming Yang, Jaime Carbonell, Quoc V Le, and Ruslan Salakhutdinov. 2019. Transformer-xl: Attentive language models beyond a fixed-length context. arXiv preprint arXiv:1901.02860.

Sumanth Dathathri, Andrea Madotto, Janice Lan, Jane Hung, Eric Frank, Piero Molino, Jason Yosinski, and Rosanne Liu. 2019. Plug and play language models: a simple approach to controlled text generation. arXiv preprint arXiv:1912.02164.

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.

Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2019. Unified language model pre-training for natural language understanding and generation. In Advances in Neural Information Processing Systems, pages 13042–13054.

Sergey Edunov, Myle Ott, Michael Auli, and David Grangier. 2018. Understanding back-translation at scale. arXiv preprint arXiv:1808.09381.

Jessica Ficler and Yoav Goldberg. 2017. Controlling linguistic style aspects in neural language generation. arXiv preprint arXiv:1707.02633.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2019. The curious case of neural text degeneration. arXiv preprint arXiv:1904.09751.

Zhiting Hu, Zichao Yang, Xiaodan Liang, Ruslan Salakhutdinov, and Eric P Xing. 2017. Toward controlled generation of text. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pages 1587–1596. JMLR. org.

Nitish Shirish Keskar, Bryan McCann, Lav R Varshney, Caiming Xiong, and Richard Socher. 2019. Ctrl: A conditional transformer language model for controllable generation. arXiv preprint arXiv:1909.05858.

Ilia Kulikov, Alexander Miller, Kyunghyun Cho, and Jason Weston. 2019. Importance of search and evaluation strategies in neural dialogue modeling. In Proceedings of the 12th International Conference on Natural Language Generation, pages 76–87.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.

Yang Liu. 2019. Fine-tune bert for extractive summarization. arXiv preprint arXiv:1903.10318.

Lajanugen Logeswaran, Honglak Lee, and Samy Bengio. 2018. Content preserving text generation with attribute controls. In Advances in Neural Information Processing Systems, pages 5103–5113.

Fuli Luo, Damai Dai, Pengcheng Yang, Tianyu Liu, Baobao Chang, Zhifang Sui, and Xu Sun. 2019. Learning to control the fine-grained sentiment for story ending generation.
A Vaswani, N Shazeer, N Parmar, J Uszkoreit, L Jones, AN Gomez, L Kaiser, and I Polosukhin. 2017. Attention is all you need. arXiv preprint arXiv:1706.03762.

Yilin Yang, Liang Huang, and Mingbo Ma. 2018. Breaking the beam search curse: A study of (re-)scoring methods and stopping criteria for neural machine translation. arXiv preprint arXiv:1808.09582.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems, pages 5754–5764.

Lantao Yu, Weinan Zhang, Jun Wang, and Yong Yu. 2017. Seqgan: Sequence generative adversarial nets with policy gradient. In Thirty-First AAAI Conference on Artificial Intelligence.

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 9051–9062.

Daniel M Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B Brown, Alec Radford, Dario Amodei, Paul Christiano, and Geoffrey Irving. 2019. Fine-tuning language models from human preferences. arXiv preprint arXiv:1909.08593.
A Appendix

Sample 1

Keywords: face - glenure - murder
Genre: biography, history
Size: M
Persons: Glenure, Appin, God, Catriona
Organisations: Appin
Locations: Scotland, Appin, Dean

P1: "What is this you say?" she asked. "What are you talking of?" "It is my testimony which may save an innocent life," said I, "and they will not suffer me to bear it. What would you do yourself? You know what this is, whose father lies in danger. Would you desert the poor soul? They have tried all ways with me. They have sought to bribe me; they offered me hills and valleys.

Generated P2: But they have not been in the least afraid of me, although they have known me as the murderer." "There is something I would have left to have," she said; "if they had taken me from their hands. You shall die." "O my soul!" she cried. "What am I to die at that?" Her father, who had a mother’s love, would have killed a slave in the bush; and that was the case. "If you see me here, you’ll know the difference between us.” He had gone, at least, and she would have heard from him again. There was something he had not understood. "Well,” he said, "if that is, then I shall die; if it were not for my sake, I should have been a free man. And if I had done it, I would have died from my father’s grave, and taken my money from the country.” I had no more idea of his feelings than he had of their manners. On the night appointed, we started for Scotland. The men left us a good cabin, and entered, to their great delight.

Original P2: And to-day that sleuth-hound told me how I stood, and to what a length he would go to butcher and disgrace me. I am to be brought in a party to the murder; I am to have held Glenure in talk for money and old clothes; I am to be killed and shamed. If this is the way I am to fall, and me scarce a man - if this is the story to be told of me in all Scotland - if you are to believe it too, and my name is to be nothing but a by-word - Catriona, how can I go through with it? The thing’s not possible; it’s more than a man has in his heart.” I poured my words out in a whirl, one upon the other; and when I stopped I found her gazing on me with a startled face. "Glenure! It is the Appin murder,” she said softly, but with a very deep surprise. I had turned back to bear her company, and we were now come near the head of the brae above Dean village. At this word I stepped in front of her like one suddenly distracted. "For God's sake!" I cried. "for God's sake, what is this that I have done?" and carried my fists to my temples.

P3: "What made me do it? Sure, I am bewitched to say these things!" "In the name of heaven, what ails you now!" she cried. "I gave my honour," I groaned. "I gave my honour and now I have broke it. O, Catriona!” "I am asking you what it is,” she said; "was it these things you should not have spoken? And do you think I have no honour, then? or that I am one that would betray a friend?"
He could not conceive how he was to get within the unbroken facade of this place till he reached the street by a great open space of marble pavement to take hold of an afternoon train. For a moment he could not see the crowding. Then another group was seen, then another. He made his way slowly into the central path. This way he was most eager to know. He had no desire to enter the city in order to get hold of some one else, to whom he could apply as little as possible to information; and so he went at once on the long platform, hoping to reach the Council House before he was in time to receive any information that he had received from his brother or his wife. After waiting several minutes for that, the expressman, who had been most unwilling to return to the city, said that he would join the Council on the way to meet the new manager, and was even more delighted to have taken possession of his money than he had been when he went to see the London cable office and asked about the interview he had held during the afternoon. The cable service had been decided after he had left it.

Original P2: For a time he was jostled, obstructed, and endangered by men hoarse and weary with cheering his name, some of them bandaged and bloody in his cause. The frontage of the wind-vane offices was illuminated by some moving picture, but what it was he could not see, because in spite of his strenuous attempts the density of the crowd prevented his approaching it. From the fragments of speech he caught, he judged it conveyed news of the fighting about the Council House. Ignorance and indecision made him slow and ineffective in his movements. For a time he could not conceive how he was to get within the unbroken facade of this place. He made his way slowly into the midst of this mass of people, until he realised that the descending staircase of the central Way led to the interior of the buildings. This gave him a goal, but the crowding in the central path was so dense that it was long before he could reach it. And even then he encountered intricate obstruction, and had an hour of vivid argument first in this guard room and then in that before he could get a note taken to the one man of all men who was most eager to see him.

P3: His story was laughed to scorn at one place, and wiser for that, when at last he reached a second stairway he professed simply to have news of extraordinary importance for Ostrog. What it was he would not say. They sent his note reluctantly. For a long time he waited in a little room at the foot of the lift shaft, and thither at last came Lincoln, eager, apologetic, astonished. He stopped in the doorway scrutinising as if he could not see, because in spite of his strenuous attempts the density of the crowd prevented his approaching it. From the fragments of speech he caught, he judged it conveyed news of the fighting about the Council House. Ignorance and indecision made him slow and ineffective in his movements. For a time he was jostled, obstructed, and endangered by men hoarse and weary with cheering his name, some of them bandaged and bloody in his cause. The frontage of the wind-vane offices was illuminated by some moving picture, but what it was he could not see, because in spite of his strenuous attempts the density of the crowd prevented his approaching it. From the fragments of speech he caught, he judged it conveyed news of the fighting about the Council House. Ignorance and indecision made him slow and ineffective in his movements. For a time he could not conceive how he was to get within the unbroken facade of this place. He made his way slowly into the central path. This gave him a goal, but the crowding in the central path was so dense that it was long before he could reach it. And even then he encountered intricate obstruction, and had an hour of vivid argument first in this guard room and then in that before he could get a note taken to the one man of all men who was most eager to see him.

P1: Along this a disorderly swarm of people marched shouting. They were singing snatches of the song of the revolt, most of them out of tune. Here and there torches flared creating brief hysterical shadows. He asked his way and was twice puzzled by that same thick dialect. His third attempt won an answer he could understand. He was two miles from the wind-vane offices in Westminster, but the way was easy to follow. When at last he did approach the district of the wind-vane offices it seemed to him, from the cheering processions that came marching along the Ways, from the tumult of rejoicing, and finally from the restoration of the lighting of the city, that the overthrow of the Council must already be accomplished. And still no news of his absence came to his ears. The re-illumination of the city came with startling abruptness. Suddenly he stood blinking, all about him men halted dazzled, and the world was incandescent. The light found him already upon the outskirts of the excited crowds that choked the Ways near the wind-vane offices, and the sense of visibility and exposure that came with it turned his colourless intention of joining Ostrog to a keen anxiety.
Figure 9: Evolution of metrics during training: it is not possible to conclude on a significant increase of the metrics during training. Bleu score drops steadily for instance. Although epoch 4 constitutes a peak in most metrics, it is difficult to assess if a proper learning is happening after epoch 1. This is quite paradoxical as the loss follows a relatively important decrease all along. It is therefore difficult to assess what is happening inside the model. Maybe it learns quickly to integrate the entities or keywords in the generated text, which is picked up by the metrics. And then improves on some less obvious dimensions, which is only captured by the loss function. Computing other metrics or changing the loss function, adapting it more to our particular problem could help us measure the true efficiency of our training. Overfitting can however be confidently excluded as training and evaluation sets remain in the same range of results at all times.
Figure 10: Metrics score distribution comparison between raw GPT-2 with and without context information. Since GPT-2 has not been trained to use the new special tokens and data layout yet, it does not perform significantly better with or without it.

Figure 11: Correlation graph between the length in characters of original and generated P2. Despite a meaningful variability, the size of original paragraphs (unknown to the model) is strongly correlated to the size of generated paragraphs, without hard-coding size categories in generation methods.