NEURAL LANGUAGE MODEL FOR AUTOMATED CLASSIFICATION OF ELECTRONIC MEDICAL RECORDS AT THE EMERGENCY ROOM. THE SIGNIFICANT BENEFIT OF UNSUPERVISED GENERATIVE PRE-TRAINING

ABSTRACT

The French TARPON project aims to build a national injury surveillance system based on emergency room (ER) visit reports. To this end, it is necessary to develop a coding system capable of classifying the causes of these visits based on the automatic reading of clinical notes written by emergency room clinicians. While supervised learning techniques have shown good results in this area, they require manual coding of a large number of texts in order to build a sufficiently large learning annotated sample. New levels of performance have been recently achieved in neural language models (NLM) over the past two years with the use of models based on the Transformer architecture with an unsupervised generative pre-training step. Our hypothesis is that methods involving a generative self-supervised pre-training step significantly reduce the number of annotated samples required for the supervised fine-tuning phase.

To measure the potential gain in terms of manual annotation work obtained by adopting this pre-training step, we exploited the fact that we could derive from available diagnostic codes the traumatic/non-traumatic nature of the cause of the ER visit. We then designed a case study to predict from free text clinical notes whether a given ER visit was the consequence of a traumatic or a non-traumatic event. We compared two strategies: Strategy A consisted in training the GPT-2 NLM on the training dataset (with a maximum of 161,930 samples) with all labels (trauma/non-trauma) in a single fully-supervised phase. In Strategy B, we split the training dataset in two parts, a large one of 151,930 samples without any label for the self-supervised pre-training phase and a much smaller one (up to 10,000 samples) for the supervised fine-tuning with labels.

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The results showed that in Strategy A, AUC and F1 score reach 0.97 and 0.89 respectively after the processing of 40,000 samples. The use of generative pre-training (Strategy B) achieved an AUC of 0.93 and an F1-score of 0.80 after the processing of only 120 samples. The same performance was achieved with only 30 labeled samples processed 3 times (3 epochs of learning). To conclude, it is possible to easily adapt a multi-purpose NLM model such as the GPT-2 to create a powerful tool for classification of free-text notes with the need of a very small number of labeled samples.

Keywords Neural Language Model · pre-training · Transformer · GPT-2

1 Background

Over the past 10 years, neural language models (NLMs) have progressively taken the largest share in the field of natural language processing with techniques based on long short-term memory and gated recurrent networks [1] or convolutional networks [2]. NLMs have then become indispensable in this field with applications for machine translation, document classification, text summary and speech recognition.

The benefit of unsupervised pre-training have been quickly identified [3] but in the domain of NLMs, new levels of performance have only been recently achieved with the use of models based on the Transformer architecture [4] with an unsupervised generative pre-training step [5]. One of the latest examples is the GPT-2, published in February 2019 by OpenAI, a large transformer-based language model with 1.5 billion parameters, pre-trained on a dataset of 8 million web pages to predict the next word after a given prompt sentence [6]. This work quickly attracted attention because the authors demonstrated the ability of the model to generate artificial texts that are difficult to distinguish from texts written by humans. Moreover, the meaning of these artificial sentences was surprisingly consistent with the original text, used as prompt. Although only a reduced version of the original model has been made public, its applications are already potentially numerous. Indeed, beyond the capability to produce coherent texts, the GPT-2, has the potential to perform tasks such as question answering and document classification. Following the same idea as the BERT model [7], transferring many self-attention blocks from a pre-trained model proved sufficient to transfer contextual representations in the dataset.

The training of the model is then performed in two distinct phases [8]: a first generative pre-training unsupervised (or more accurately called self-supervised) phase, consists in the exploitation of a corpus of texts which leads to the automatic text production capability, the relevance of which indicating that the networks learned contextual representations. A second supervised fine-tuning phase consists in resuming learning from a corpus of annotated texts with the objective of creating a system that allows the realization of a specific task.

We intended to leverage the document classification potential of GPT-2 to classify free-text clinical notes in the context of a project TARPON. This French project proposes to build a national surveillance system based on the exhaustive collection of emergency room (ER) visits reports in France. Its main feature is to apply automatic language analysis to extract injury mechanisms and causes from the computerized medical record information produced by the medical staff as free text for each visit. The creation of this database and its matching with the French national health data system will be used to create a nation-wide comprehensive and automated trauma monitoring, research and alert system. More than 21 million un-labeled clinical notes from the emergency room are produced every year in France. The cause for the visit is not available as a standardized database although fully described in free text computerized clinical reports. The overall project objective is to develop a tool that would derive standardized data describing injury mechanisms and causes from these notes. To that purpose, substantial amounts of manually annotated data would be necessary to train a conventional model.

Our hypothesis is that methods involving a generative self-supervised pre-training step such as the GPT-2 significantly reduce the number of annotated samples required for the supervised fine-tuning phase. This is of paramount importance for all projects wishing to use NLMs models for free-text classification tasks because the manual annotation phase is by far the most expensive one. The objective of our study is therefore to measure the gain in terms of manual annotation work obtained by adopting this pre-training step.

2 Methods

2.1 Study overview

To test our hypothesis, we exploited the fact that we could derived the traumatic/non-traumatic nature of the cause of the ER visit from available diagnostic codes assigned by clinicians or technical staff at the time of the patient’s hospitalization. We then designed a case study to assess whether we can also predict the traumatic/non-traumatic
nature of the cause of the ER visit from computerized free text clinical notes. The traumatic/non-traumatic cause of the visit derived from diagnostic codes are used here as the labels.

Figure 1: *Strategy A*: supervised training

In order to measure the gain offered by a self-supervised training phase, we compared the performance of two strategies (Figures 1 and 2). *Strategy A* consisted in training the GPT-2 NLM on our full training dataset with all labels in a single fully-supervised phase. In *Strategy B*, we split the training dataset in two parts, a large one without any label for the self-supervised pre-training phase and a much smaller one for the supervised fine-tuning with labels. The main question was therefore to assess how many samples will be necessary in this fine-tuning part of *Strategy B* to achieve the same performance as in *Strategy A*. This should give us a measure of how much annotation work will be saved as a result of *Strategy B*.

2.2 Dataset

We retrieved clinical notes and International Classification of Diseases diagnostic codes, version 10 (ICD-10) from the automatic computerized system of the adult ER of the University Hospital of Bordeaux in France from 2011 to
2018. The ICD-10 [9] is the most used standardized way of indicating diagnoses and medical procedures, and is the terminology mandatorily used in France for all stays in private or public hospitals.

The data set contains medical records of 288,404 visits of which 209,341 contain both diagnosis code and clinical note. The label (trauma / non-trauma event) was derived from the ICD-10 code: a total of 56,410 visits with an ICD-10 code beginning with letters S, T1 to T35 and V were coded as trauma and 115,520 visits with an ICD-10 code beginning with letters A, C, D, E, G, H, I, J, L, N were coded as non-trauma. A total of 37,411 visits with codes beginning with other letters (F, M, O, P, Q, T36 to T98, X40 to X57, Y10 to Y98, U, Z) were excluded because they correspond to pathologies for which the traumatic nature is either uncertain or discussed from a semantic point of view. The total study sample size was therefore 171,930.

A random sample of 10,000 clinical notes was selected for validation. The samples from a remaining dataset with 161,930 notes were first used with labels in Strategy A in order to estimate the number of samples needed to achieve maximum prediction performance on the 10,000-sample validation set. For the second Strategy, we further split the 161,930 notes into a sample of 151,930 notes with no label for unsupervised pre-training with 3 epochs and a second dataset with a maximum number of 10,000 samples with labels for the supervised fine-tuning step.

2.3 Model

Like Neural Language models based on convolution and recurrent networks, the GPT-2 proposed by Radford and colleagues is a sequence to sequence [10] transduction model. The new feature is that it is built on a Transformer architecture [4]. The main feature of the Transformer architecture is to use attention weight on text inputs. During the training process, the network learns a context vector which gives global level information on inputs telling where attention should be focused. The novel approach is to eliminate recurrence completely and replace it with attention to handle the dependencies between input and output.

The GPT-2 has been developed in order to allow its application to a wide range of undefined problems. This model is designed to predict the next token from the input of a text sequence. By looping this process, it then functions as an artificial text generator. This text can be generated de novo or from an arbitrary portion of text called "prompt". The model is trained on millions of webpages without any explicit supervision. There are 4 versions of GPT-2 with respectively 117, 345, 762 and 1542 million parameters. Only the two smallest ones are trainable on standard workstations. Their model files are respectively 0.49 and 1.42GB in size.

The models were trained on web text mostly written in English while our clinical notes are in French. Consequently, we did not in the present work use those pre-trained models and started training from a random set of weights.

2.4 Text representation and input format

The authors of the GPT-2 chose a modified version of the Byte Pair Encoding method [11] which is a middle ground between word level encoding for frequent symbol sequences and character level encoding for infrequent symbol sequences. The evaluation of GPT-2 on its ability to predict the final word of sentences (this ability requires modeling long-range dependencies in text) showed that the accuracy was significantly improved by adding a stop-word filter [6].

2.5 Operating principle

In Strategy B, the pre-training step is referred to as unsupervised learning because it is derived from simply reading the text database of clinical notes, without labels (Figure 2). It actually uses a sliding learning window on the text. The first part of this window corresponds to the input and the final token corresponds to the token to be predicted. Thus, the term unsupervised could be considered as abusive and self-supervised is more appropriate. In our case study, the result is a model that can generate texts that resemble clinical notes.

For the supervised learning phases (Strategy A and second learning process in Strategy B), we added a sequence at the end of the clinical note, consisting of an arbitrary textual identifier (e.g., TARPON) followed by an arbitrary code, say 1 for clinical notes corresponding to traumatic events and 0 for clinical notes corresponding to non-traumatic events. As described above, this code was derived from the diagnosis classification manually coded by clinicians.

For both Strategies (Figures 1 and 2), the validation phase consisted in building a prompt by adding at the end of the clinical note for which we are trying to predict the TRAUMA code the arbitrary textual identifier (TARPON) and ask the model to predict the next token (here ideally 0 or 1). On the first iteration, the prediction can be any tokens but, as expected, this quickly turns to be only 0s and 1s.
2.6 Outcomes

The prediction performance of the model was measured with F1 score and area under the ROC curve statistics [12]. An evaluation on the same 10,000-sample dataset was performed every 50 iterations for Strategy A and Strategy B.

2.7 Hardware

The 117M model was trained on a PC with a single Nvidia GeForce GTX 1080 Ti GPU with 11GB of video RAM. The 345M model was trained on a PC with a single Nvidia TITAN RTX GPU with 24GB of video RAM. The training phase took about one week in each Strategy.

2.8 Ethics, Confidentiality of data

No nominative data were necessary for this work. Data were also not indirectly nominative as no admission date or time were used. The dataset was however not specifically de-identified. Data processing and computing were conducted within the facilities of the Emergency Department of the Bordeaux University Hospital.

3 Results

We compared in Figure 3 and Figure 4 Strategy A (fully supervised training without pre-training) and B (supervised training with pre-training) by plotting AUC and F1 by iterations with a batch size of 1 case read per iteration. In Strategy A, AUC and F1 score reach the values of 0.97 and 0.89 respectively after the processing of 40,000 samples. The use of generative pre-training (Strategy B) achieved an AUC of 0.93 and an F1-score of 0.80 after the processing of only 120 samples (Figure 5). The same performance was achieved with only 30 labeled samples processed 3 times (3 epochs of learning).

![supervised, AUC](image)

![2-step AUC](image)

Figure 3: Area under the ROC curve (AUC) in Strategy A (supervised) and Strategy B (2-step).

Comparing 117M and 345M GPT-2 models, it showed no significant improvement using a more complex model.

4 Discussion

As suggested by Radford and colleagues [8], large gains could be realized by generative pre-training on a corpus of unlabeled text, saving a large amount of labeling work. Our example of clinical notes classification task, the order of magnitude is a factor of 400. In their work, Radford and colleagues reported an improvement of 8.9% on commonsense reasoning (Stories Cloze Test), 5.7% on question answering (RACE), and 1.5% on textual entailment (MultiNLI) [8].

These results are in line with recent work that showed that self-supervised pre-training methods, such as ELMo [13] and BERT [7], have established a qualitatively new level of performance in most widely used Natural Language Understanding benchmarks. Howard and Ruder [14] in particular report very similar results in a comparable text...
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classification task, with a model that matches with only 100 labeled examples the performance of training from scratch on 400x more data. While the extensive use of pre-trained word embeddings could be considered as of the same nature of generative pre-training, the gain provided by generative pre-training is a major step for those who seek to classify free text document with minimal manual coding efforts.

We have benefited from the work of the researchers who published the GPT-2 model, which still seems to be the most efficient today. Other models have been and will be proposed and strategies for classification will need to be updated. Recent and promising work includes the work of Yang and colleagues and their XLNet model [15] which currently ranks first at the Stanford Question Answering Dataset (SQuAD2.0, rajpurkar.github.io/SQuAD-explorer).

Probably because the GPT-2 model was only recently made public, very few applications have been published today. However, this type of tool will probably be extensively used in the near future for a wide range of tasks. In the area of document classification alone, they will likely provide faster and more relevant access to information. Certainly, these applications will go beyond simple classification tasks. The 345M GPT-2 model did not generate significantly better results than the 117M model. The use of larger models could bring further improvement, which could have been tested should we had access to the necessary computing power. Unfortunately, this was not the case and we will have to be satisfied with the results presented here.
In this study, we used as a reference a label based on the ICD-10 codes. Although indirect, this gold-standard is always reliable should we stick to the sub-set of diagnoses we selected. This method has had the advantage of providing us with a large amount of labeled data but does not allow us to compare the model’s performance with human annotation.

5 Conclusion

Our work shows that it is possible to easily adapt a multi-purpose NLM model such as the GPT-2 to create a powerful classification tool of free-text notes. The self-supervised training phase appeared to be a very powerful tool to dramatically decrease the number of labeled samples needed for supervised learning. These results will be used in the coming months to implement the exhaustive coding of all events leading to trauma with emergency room visits, making it possible to build a national trauma observatory within the TARPO project. More generally, this also opens broad perspectives for those interested in free-text automatic coding. In the field of health, this will be particularly useful for diagnosis coding, clinical report classification and patient reports analysis.

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