From FREEM to D’AlemBERT: a Large Corpus and a Language Model for Early Modern French

Simon Gabay\textsuperscript{3}, Pedro Ortiz Suarez\textsuperscript{1,2}, Alexandre Bartz\textsuperscript{2}, Alix Chagué\textsuperscript{1}
Rachel Bawden\textsuperscript{1}, Philippe Gambette\textsuperscript{3}, Benoît Sagot\textsuperscript{1}

Inria\textsuperscript{1}, Sorbonne Université\textsuperscript{2}, Université de Genève\textsuperscript{3}, LIGM, Université Gustave Eiffel, CNRS\textsuperscript{4}
2 rue Simone Iff, 75012 Paris (France)\textsuperscript{1}, 21 rue de l’École de médecine, 75006 Paris (France)\textsuperscript{2}, rue du Général-Dufour 24, 1211 Genève (Switzerland)\textsuperscript{3}, 5 boulevard Descartes, F-77454 Champs-sur-Marne (France)\textsuperscript{4}
\{pedro.ortiz, alix.chague, benoit.sagot, rachel.bawden\} @inria.fr\textsuperscript{1}, alexandre.bartz@sorbonne-universite.fr\textsuperscript{2}, simon.gabay@unige.ch\textsuperscript{1}, philippe.gambette@univ-eiffel.fr\textsuperscript{4}

Abstract

Language models for historical states of language are becoming increasingly important to allow the optimal digitisation and analysis of old textual sources. Because these historical states are at the same time more complex to process and more scarce in the corpora available, specific efforts are necessary to train natural language processing (NLP) tools adapted to the data. In this paper, we present our efforts to develop NLP tools for Early Modern French (historical French from the 16\textsuperscript{th} to the 18\textsuperscript{th} centuries). We present the FREEM\textsubscript{max} corpus of Early Modern French and D’AlemBERT, a RoBERTa-based language model trained on FREEM\textsubscript{max}. We evaluate the usefulness of D’AlemBERT by fine-tuning it on a part-of-speech tagging task, outperforming previous work on the test set. Importantly, we find evidence for the transfer learning capacity of the language model, since its performance on lesser-resourced time periods appears to have been boosted by the more resourced ones. We release D’AlemBERT and the open-sourced subpart of the FREEM\textsubscript{max} corpus.

Keywords: Digital humanities, Early Modern French, Language modelling, Neural language representation models, Less-resourced languages, Corpus creation, POS tagging

1. Introduction

With the rise of digital humanities, it is becoming increasingly important to develop high quality tools to automatically process old states of languages. Libraries, archives and museums, among others, are digitising large numbers of historical sources, from which high quality data must be extracted for further study by specialists of human sciences. We mention new approaches such as “distant reading” (Moretti, 2013). Many (sub)tasks such as automatic OCR post-correction (Rijhwani et al., 2021) and linguistic annotation (Camps et al., 2020) benefit from pretrained language models to improve their accuracy, and this is what motivated us to develop a BERT-like (Devlin et al., 2019) contextualised language model for Early Modern French.

Languages evolve over time on many different levels: from one century to another, we see variations in spelling, syntax, the lexicon etc. However this variation is not uniform: it tends, at least for “literate scriptors” (literature, journalism, law, etc.), to converge towards a single norm over time, and this has especially been the case for French because of the prominent role of the Académie française and the remarqueurs (Ayres-Bennett and Seijido, 2011). The result of this convergence is, for instance, that spelling and word order within sentences have become more strict, where they were less so in the past. From a computational perspective, historical states of language are therefore not only different from the contemporary state, but, from a computational perspective, are also more complex because they do not follow a strict and explicit norm. In French, this explicit norm appeared in the 17\textsuperscript{th} c. and was slowly integrated throughout the 18\textsuperscript{th} c.

On top of this first linguistic problem, a second issue appears: because the production of textual sources has continued to grow exponentially, it is easier to collect a corpus for contemporary French than for the 19\textsuperscript{th} c. French, which is itself easier than for the 18\textsuperscript{th} c. French, etc. The further we go back in time, the more scarce resources are, which creates the following paradox: we have more data when the language is homogeneous and simple for the computer to process, and less when it is heterogeneous and harder to process.

The following paper will address the development of D’AlemBERT, a neural language model in a complex setting, defined here as the state of language with scarce heterogeneous resources. We will also present FREEM\textsubscript{max} the data used to train the model, discuss its conception, and evaluate its efficiency with a classical natural language processing (NLP) task, part-of-speech (POS) tagging, crucial for corpus linguistics and the digital humanities. We release both the D’AlemBERT model and a subset of the FREEM\textsubscript{max} dataset that we were allowed to open source by the original authors.

2. Related Work

Large datasets for historical states of languages or extinct languages do exist. The Corpus Middelnederlands for Medieval Dutch (Reenen, Pieter van and Mulder, Maaike, 1998) and the Base Geste for Medieval French, this explicit norm appeared in the 17\textsuperscript{th} c. and was slowly integrated throughout the 18\textsuperscript{th} c.
French (Camps et al., 2019) are freely available online, encoded in TEL. It is also the case for other corpora for later states of language, such as the Reference corpus of historical Slovene, covering approximately three centuries of Slovene (1584–1899) (Erjavec, 2015), and the “corpus noyau” of Presto (Blumenthal and Vigier, 2018). This last corpus, in its extended version, uses other French corpora such as Espistemon for Renaissance French (Demonet, 1998) and the University of Chicago’s American and French Research on the Treasury of the French Language (ARTFL) (Morrissey and Olsen, 1981); or like FRANTEXT (ATILF, 1998), which is a generalist French corpus, covering the different states of the French language between the 11th and the 21st century. Although most of these text collections are free, the two biggest ones, FRANTEXT and ARTFL, are not freely available or open-sourced.

Concerning language modelling in French, two main models are available for contemporary French, CamemBERT (Martin et al., 2020) and FlauBERT (Le et al., 2020). CamemBERT was trained on a freely available, automatically web-crawled corpus called OSCAR (Ortiz Súarez et al., 2019) while FlauBERT was trained on a mix of web-crawled data and manually curated (partly non freely available) contemporary French corpora. Neither of these models was explicitly pre-trained for historical French. However efficient language models have been trained for less-resourced or extinct Languages such as Latin (Bamman and Burns, 2020), following the approach of Martin et al. (2020) for training language models with less data than was previously thought. There have also been some recent projects that specifically target Early Modern French such as that of Pie Extended (Clérice, 2020) that uses the hierarchical encoding architecture originally proposed by Manjavacas et al. (2019) which itself is constructed by stacking multiple Bi-LSTM-CRFs. Clérice (2020) distributes pre-trained models for POS tagging and lemmatisation.

3. Corpora
For the past few years, we have been involved in the development of linguistic resources for Early Modern French. The initiative, called FreEM (which stands for FRENch Early Modern), aims to collect the corpora required for various NLP tasks such as lemmatisation, POS tagging, linguistic normalisation and named entity recognition. Two of these corpora are introduced here: FreEMmax and FreEMEP (see Section 3.3).

3.1. Early Modern French
Experiments are based on data of which the core comprises Early Modern French literary texts. We loosely define Early Modern French as a state of language following Middle French in 1500—following here the terminus ad quem used by the Dictionnaire de Moyen Français (Martin, Robert (dir.), 2020)—and ending with the French Revolution in 1789. It therefore encompasses three centuries (16th, 17th and 18th c.), or two linguistic periods: the français préclassique or “preclassical French”; 1500–1630 and the français classique or “classical French”, 1630–1869; both periodisations are currently used in French linguistics (e.g. by Vachon (2010) and Amatuzzi et al. (2019)). A typical example of Early Modern French, taken from Guez de Balzac (1624), is given in Table [1]. We note here the presence of several phenomena that have now disappeared in contemporary French, such as the presence of abbreviations (dët→dont), the long s (I, see milières), the use of u instead of u (vne for une), the conservation of etymological letters (votre→Latin vōster rather than votre) and calligraphic letters (γ in Surquoy), the absence of welding (mal-heures and not malheurs) and the opposite (Surquoy and not Sur quoi).

For NLP tasks, which process raw sequences, such differences with respect to contemporary French are not trivial, and they prevent the processing of historical texts with tools trained on recent sources.

3.2. FreEMmax
Usable historical documents are difficult to find because, as previously mentioned, they are more rare than contemporary ones; editors tend to normalise the language (i.e. use the spelling conventions of contemporary French, see Gabay, 2014, transcriptions are not always) distributed in a digital format. FreEMmax (Gabay et al., 2022) is an attempt to solve this problem, and the aim of this dataset is to group together the largest number or texts possible written in Early Modern French. The texts have a variety of sources, which can be grouped into three main types:

- Two institutional datasets have been used and are non open-sourced:
  - FRANTEXT intégral (ATILF, 1998 b), the biggest database of French texts (only the texts between 1500 and 1800), a very small portion of which is open access: FRANTEXT Démonstration (ATILF, 1998 a);
  - Electronic Enlightenment (Bodleian Libraries, 2008 ), an online collection of edited correspondences of the Early Modern period;
- Several come from research projects distributing transcriptions online;

1Note however that texts in Old, Middle and Modern French do exist in the internet, and might have found their way to the training corpus of these two models. This is especially the case for Modern French texts, which automatic language classification tools can easily classify as Contemporary French.
Surquoy, SIRE, s’il plaît à voire
Maïesté de le fouëren des miséres de
fon Eftat, dôt au moins ell’a tiré cét
advantage, qu’en vne grande ieunesfe
ell’a acquis vne grande expericé, elle
verra que tous les malheurs de son bas
âge ont pris leur commencement en
semblables occasions ;

“Whereupon, SIR, if it pleases your
Majesty to remember the miseries of
her state, from which at least she has
derived this advantage, that in great
youth she has acquired great experi-
ence, she will see that all the misfor-
tunes of her early life took their begin-
ing on similar occasions;”

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Table 1: Example of normalisation taken from the Lettres de Guez de Balzac (1624).

| Source | Normalised | Translation |
|--------|------------|-------------|
| The Antonomaz project, French mazarinades (https://cahier.hypotheses.org/antonomaz); | | |
| The II.B section (in French) of the Actis Pacis Westphalicae, diplomatic letters for the Peace of Westphalia (http://kaskade.dwds.de/dstar/apwcf/); | | |
| The Bibliothèques virtuelles humanistes, 16th c. French literature (http://www.bvh.univ-tours.fr); | | |
| The Corpus électronique de la première modernité, 17th c. French literature (http://www.cepem.paris-sorbonne.fr); | | |
| The Condé project, coutumiers normands (https://conde.hypotheses.org); | | |
| The Corpus Descartes, works of René Descartes (https://www.unicaen.fr/puc/sources/prodescartes/); | | |
| The Bibliothèque dramatique of the CELLF, 17th c. French plays (http://bibdramatique.huma-num.fr); | | |
| The Fabula numerica project, French fables (https://obvill.sorbonne-universite.fr/projets/fabula-numerica); | | |
| The Fonds Boissy, plays of Louis de Boissy (https://www.licorn-research.fr/Boissy.html); | | |
| The Mercure Galant project, the famous French gazette and literary magazine between 1672 and 1710 (https://obvill.sorbonne-universite.fr/corpus/mercure-galant); | | |
| The Rousseau online project, works of Jean-Jacques Rousseau (https://www.rousseauonline.ch); | | |
| The Sermo project, sermons of the 16th and 17th c. (http://sermo.unine.ch); | | |
| The Théâtre classique project, 17th and 18th c. French plays (http://www.theatre-classique.fr); | | |

• Additional sources come from researchers who kindly accepted to offer their personal transcriptions or data scrapped by our team:
  - Transcriptions of Anne-Élisabeth Spica (17th c. French novels);
  - Transcriptions found on Wikisource (https://fr.wikisource.org);
  - Transcriptions (ePub files) found on Gallica (https://gallica.bnf.fr);
  - Transcriptions found on various websites online.

Additional data for later states of the language, up to the 1920’s (mainly from FRANTEXT intégral), are also provided for two main reasons: on the one hand, it is common to normalise Early Modern French into Contemporary French (Gabay, 2014) because of the linguistic proximity between these the two states of the language, and on the other hand, it helps to collect (precious) additional data to avoid ending up with too small of a corpus for our needs.

The final result is far from being balanced or representative (see Figure 1). 16th c. French documents are under-represented, as well as 18th c. literature. The 17th c. is clearly over-represented, especially its second half—probably one of the most important of French literature, which could explain this situation (on top of our personal interest for this specific period). As some texts are still (partially) protected by restrictive licences, the FREEMax corpus exists in both open and non-open versions, only the open one being distributed. In order to limit the impact of licences forbidding the modification of files, we have designed a pipeline to distribute the data as it was found and recreate it (see Figure 2).

Metadata is prepared manually in order to have the same categories for each document, whatever its origin. As well as the author, the title and the date (where relevant), we also provide the genre (“theatre”), sometimes a subgenre (“tragedy”), the linguistic status (normalised or not) and the licence attached to the transcription.
### Table 2: Breakdown of the FReEM\textsubscript{max} corpus by text origin.

| Origin                                           | #Tokens   |
|--------------------------------------------------|-----------|
| Spica corpus                                     | 691,467   |
| Antonomaz project                               | 119,194   |
| Acta Pacis Westphlicae II B                     | 2,463,047 |
| Bibliothèque Bleue                              | 776,838   |
| BVH                                              | 2,434,657 |
| CEPM                                             | 2,707,432 |
| Condé project                                    | 3,173,845 |
| Descartes                                        | 1,025,337 |
| CELLF                                           | 1,873,772 |
| Electronic enlightenment                         | 6,568,047 |
| Fabula project                                   | 145,978   |
| FRANTEXT intégral (>1500, <1800)                 | 60,018,390|
| FRANTEXT intégral (>1800)                        | 71,504,440|
| FRANTEXT Démonstration                           | 1,255,454 |
| Gallica                                         | 5,212,333 |
| Boissy project                                   | 438,215   |
| Mercure galant                                  | 5,427,469 |
| Rousseau Online project                          | 2,428,587 |
| Scrapping                                        | 1,936,835 |
| Sermo project                                    | 529,647   |
| Théâtre classique project                        | 13,916,169|
| Wikisource                                       | 996,329   |
| **TOTAL**                                        | 185,643,482|

Figure 1: Distribution of the documents in the FReEM\textsubscript{max} corpus per year

3.3. FReEM\textsubscript{LPM}

The FReEM\textsubscript{LPM} ("Lemma, POS tags, Morphology") has already been presented (Gabay \textit{et al.}, 2020). The POS-annotated data is a mixture of two different sources. On the one hand, there is the CornMol corpus (Camps \textit{et al.}, 2020), made up of normalised 17\textsuperscript{th} c. French comedies. On the other hand, there is a gold subset of the Presto corpus (Blumenthal \textit{et al.}, 2017), made up of texts of different genres written during the 16\textsuperscript{th}, 17\textsuperscript{th} and 18\textsuperscript{th} c., which have previously used to train annotation tools (Diwersy \textit{et al.}, 2017), and was heavily corrected by us to match our annotation principles (Gabay \textit{et al.}, 2020).

On top of traditional in-domain tests, an out-of-domain testing dataset was prepared to control the capacity of the model to generalise to other genres and periods. Centuries covered are the 16\textsuperscript{th}, 17\textsuperscript{th}, 18\textsuperscript{th}, 19\textsuperscript{th} and 20\textsuperscript{th}. There are two test sets for each century: one made up only of theatre, the other of everything but theatre. Each test set comprises 10 short samples (c. 100 tokens), as representative as possible of the linguistic production of the century (female and male authors, decade of publication, genre, etc.). All the data from FReEM\textsubscript{LPM} (but almost none of the out-of-domain) can be found in FReEM\textsubscript{max}.

4. D’AlemBERT: a neural language model for Early Modern French

In this section, we describe the pretraining data, architecture, training objective and optimisation setup we use for D’AlemBERT, our new neural language model for Early Modern French.

4.1. Pre-processing

Similar to RoBERTa (Liu \textit{et al.}, 2019) we segment the input text data into subword units using Byte-Pair encoding (BPE) (Sennrich \textit{et al.}, 2016) in the implementation proposed by (Radford \textit{et al.}, 2018) that uses bytes instead of unicode characters as the base subword units. The BPE encoding does not require pre-tokenisation (at the word or token level), thus removing the need to develop a specific tokeniser for Early Modern French. We use a vocabulary size of 32,768 subword tokens. These subwords are learned on the entire FReEM\textsubscript{max} dataset.
with the RoBERTa (Liu et al., 2019), as our model diverged for 10k steps up to a peak value of $\beta_2 = 0.0003$ instead of the original 0.0001 used by the original implementation of RoBERTa (Liu et al., 2019), as our model diverged with the 0.0001 value. We hypothesise that this is either due to the smaller size of $\text{FREEM}_{\text{LPM}}$ (compared to the corpora used for RoBERTa or CamemBERT) or to our large batch size. We train our model for 31k steps, which amounts to 41 epochs. The total pre-training times, the details of the infrastructure we used and even the carbon emissions of our model are reported in Appendix A.

### 5. Evaluation and Discussion

In order to evaluate our D’AlemBERT model, we fine-tune it for POS tagging on the $\text{FREEM}_{\text{LPM}}$ corpus. We use the flair framework\footnote{https://github.com/flairNLP/flair} for sequence tagging (Akbik et al., 2019). To fine-tune D’AlemBERT for POS we follow the same approach as Schweter and Akbik (2020) with some modifications: we append a linear layer of size 256 that takes as input the last hidden representation of the $<s>$ special token and the mean of the last hidden representation of the subword units of each token (token as defined for $\text{FREEM}_{\text{LPM}}$), that is, we use a “mean” subword pooling strategy. We fine-tune D’AlemBERT with a learning rate of 0.000005 for a total of 10 epochs. We also fine-tune CamemBERT using the exact same hyperparameters as that we use for D’AlemBERT.

$\text{FREEM}_{\text{LPM}}$ provides a standard split (train, dev, test), however it also proposes an evaluation on a out-of-domain subcorpus that is not contained in the standard split and that is separated by century (from the 16th to the 20th century) and that also contains both the Normalised and Original versions of the texts for the 16th, 17th and 18th centuries. The idea of this out-of-domain evaluation corpus is to have a fine-grained evaluation of the models to better assess their performance in all the different types of text that one might encounter when working with Early Modern French data. Following the approach of Clerice (2020), we report the scores obtained on the out-of-domain testing dataset of $\text{FREEM}_{\text{LPM}}$ in Table 3. We use the scores previously reported by Clerice (2020) using Pie Extended as our baseline as well as the fine-tuned CamemBERT that serves as a second baseline as well as a rough estimation of how much knowledge can D’AlemBERT transfer from the $\text{FREEM}_{\text{max}}$ into this task.

### 4.2. Language Modelling

**Transformer** D’AlemBERT uses the exact same architecture as RoBERTa, which is a multi-layer bidirectional Transformer (Vaswani et al., 2017). D’AlemBERT uses the original base architecture of RoBERTa (12 layers, 768 hidden dimensions, 12 attention heads, 110M parameters).

**Pretraining Objective** We train our model on the Masked Language Modelling (MLM) task as proposed by RoBERTa’s authors (Liu et al., 2019): given an input text sequence composed of $N$ tokens $x_1,...,x_N$, we select 15% of tokens for possible replacement. Among those selected tokens, 80% are replaced with a random token. The model is then trained to predict the masked tokens using cross-entropy loss.

Again, following the RoBERTa approach, we dynamically mask tokens instead of fixing them statically for the whole dataset during preprocessing. We also choose not to use the next sentence prediction (NSP) task originally used in BERT (Devlin et al., 2019), as it has been shown that it does not improve downstream task performance (Conneau and Lample, 2019)\footnote{https://github.com/LoicGrobol/zeldarose} (Liu et al., 2019).

**Optimisation** We optimise our model in the exact same way as (Liu et al., 2019) using Adam (Kingma and Ba, 2015) ($\beta_1 = 0.9$, $\beta_2 = 0.98$) for 100k steps with large batch sizes of 8,192 sequences, each sequence containing at most 512 tokens.

**Pre-training** We use the RoBERTa implementation in the Zelda Rose library\footnote{https://github.com/LoicGrobol/zeldarose} and again, in the same way as Liu et al. (2019) our learning rate is warmed up for 10k steps up to a peak value of 0.0003 instead of the original 0.0001 used by the original implementation of RoBERTa (Liu et al., 2019), as our model diverged with the 0.0001 value. We hypothesise that this is either due to the smaller size of $\text{FREEM}_{\text{max}}$ (compared to the corpora used for RoBERTa or CamemBERT) or to our large batch size. We train our model for 31k steps, which amounts to 41 epochs. The total pre-training times, the details of the infrastructure we used and even the carbon emissions of our model are reported in Appendix A.

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$\text{FREEM}_{\text{LPM}}$ provides a standard split (train, dev, test), however it also proposes an evaluation on a out-of-domain subcorpus that is not contained in the standard split and that is separated by century (from the 16th to the 20th century) and that also contains both the Normalised and Original versions of the texts for the 16th, 17th and 18th centuries. The idea of this out-of-domain evaluation corpus is to have a fine-grained evaluation of the models to better assess their performance in all the different types of text that one might encounter when working with Early Modern French data. Following the approach of Clerice (2020), we report the scores obtained on the out-of-domain testing dataset of $\text{FREEM}_{\text{LPM}}$ in Table 3. We use the scores previously reported by Clerice (2020) using Pie Extended as our baseline as well as the fine-tuned CamemBERT that serves as a second baseline as well as a rough estimation of how much knowledge can D’AlemBERT transfer from the $\text{FREEM}_{\text{max}}$ into this task.

| Model       | Original | Normalised or Contemporary |
|-------------|----------|----------------------------|
| Drama       | 16       | 17 | 18 | 19 | 20 | Avg   |
| Pie Extended | 90.34 | 94.47 | 94.64 | - | - | 93.15 |
| CamemBERT   | 87.06 | 89.01 | 90.92 | - | - | 89.00 |
| D’AlemBERT  | 94.17 | 96.59 | 96.28 | - | - | 95.68 |
| Varia       | 95.24 | 95.75 | 96.61 | 95.03 | 93.71 | 94.76 |
|              | 94.52 | 96.64 | 96.88 | 94.90 | 95.30 | 95.65 |
|              | 95.59 | 96.81 | 96.84 | 95.58 | 95.15 | 95.95 |

Table 3: Comparison between D’AlemBERT, CamemBERT and Pie Extended performance on $\text{FREEM}_{\text{LPM}}$.\footnotetext{\footnote{https://github.com/LoicGrobol/zeldarose}}\footnotetext{https://github.com/flairNLP/flair}
We can see that D’AlemBERT consistently outperforms Pie Extended and CamemBERT in both the normalised and original versions of our out-of-domain testing data and for all different periods by a considerable margin. We can also see that on average the difference in score between D’AlemBERT and Pie Extended is greater for the original split than the normalised one. This suggests that D’AlemBERT can generalise more effectively to non-normalised data than the more traditional architecture used by Pie Extended. Moreover we can also see that the difference in scores is also greater for the 16th c. and 17th c. data. This is interesting, especially for the 16th c., because, as we can see in Figure 1, this is the least represented period in the FREEM\text{\textsubscript{max}} corpus. This result actually suggests that D’AlemBERT might be able to do effective transfer learning from the 18th c., 19th c. and 20th c. data to the 16th c. and 17th c. data.

As for CamemBERT, we can see that it consistently scores lower than both D’AlemBERT and Pie Extended. Moreover, we can see that it struggles particularly with the non-normalised data of the 16\textsuperscript{th} c., 17\textsuperscript{th} c. and 18\textsuperscript{th} c.. This results clearly shows that CamemBERT cannot easily generalised to these earlier states of languages, or at least not with the quantity of data found in the training set of FreEM\text{\textsubscript{LPM}}. These results also show the impressive capacity of D’AlemBERT of quickly generalising to diverse set of states of language, as well as its capacity to transfer knowledge from the FREEM\text{\textsubscript{max}} corpus into this task. The obtained results are also a testament to the importance of the pre-training data, specially taking in account that the pre-training set of CamemBERT is more than 100 times bigger than that of D’AlemBERT.

6. Conclusion

In this paper we presented the manually curated FREEM\text{\textsubscript{max}} corpus of Early Modern French as well as D’AlemBERT, a RoBERTa-based language model trained on FREEM\text{\textsubscript{max}}. With D’AlemBERT, we showed that it is possible to successfully train a transformer-based language model for historical French with even less data than originally shown in previous works (Martin et al., 2020). Moreover with our POS tagging evaluation we were able to observe some form of transfer learning and generalisation across multiple states of the language corresponding to different periods of time. Both our corpus and our model will be of use to digital humanists and linguists interested in Early Modern French. For our future work, we hope that will be able to study the application of our D’AlemBERT model to other NLP tasks such as text normalisation, named entity recognition and even document structuring, where we hope to more extensively study the transfer learning capabilities of our approach.

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## A. Carbon Footprint

| Model       | Power (W) | Time (h) | (PUE) kWh | CO²e (kg) |
|-------------|-----------|----------|-----------|-----------|
| Pre-train   | 48640     | 20       | 1537.02   | 46.11     |
| Evaluation  | 589       | 1        | 0.93      | 0.03      |
| **Total CO²e** |          |          |           | 46.14     |

Table 4: Average power draw, number of models trained, training times in hours, mean power consumption including power usage effectiveness (PUE), and CO² emissions; for each setting.

In light of recent interest concerning the energy consumption and carbon emission of machine learning models and specifically of those of language models [Schwartz et al., 2020; Bender et al., 2021], we have decided to report the power consumption and carbon footprint of all our experiments following the approach of Strubell et al. (2019). We report the energy consumption and carbon emissions of both the pre-training of D’AlemBERT and its evaluation.

### Pre-training:
We use a cluster of 32 machines, each having 4 GPU Nvidia Tesla V100 SXM2 32GiB, 192GiB of RAM, and two Intel Xeon Gold 6248 processors. One Nvidia Tesla V100 card is rated at around 300W, while the Xeon Gold 6248 processor is rated at 150W. For the DRAM we can use the work of Desrochers et al. (2016) to estimate the total power draw of 192GiB of RAM at around 20W. Thus, the total power draw of the pre-training adds up to around 48640W.

### Evaluation:
We use a single machine with a single GPU Nvidia Tesla V100 SXM2 32GiB, 384GiB of RAM and two Intel Xeon Gold 6226 processors. The Xeon Gold 6226 processor is rated at 125 W and the DRAM total power draw can be estimated at around 39W. Therefore, the total power draw of the evaluation adds up to around 589W.

With this information, we use the formula proposed by Strubell et al. (2019) to compute the total power required for each setting:

\[
 p_t = \frac{1.58t(c_p + p_r + g_p)}{1000}
\]

Where \( c \) and \( g \) are the number of CPUs and GPUs respectively, \( p_c \) is the average power draw (in W) from all CPU sockets, \( p_r \) the average power draw from all DRAM sockets and \( p_g \) the average power draw of a single GPU. We estimate the total power consumption by adding GPU, CPU and DRAM consumption, and then multiplying by the Power Usage Effectiveness (PUE), which accounts for the additional energy required to support the compute infrastructure. We use a PUE coefficient of 1.58, the 2018 global average for data centres (Strubell et al., 2019). In Table 4, we report the training times in hours, as well as the total power draw (in Watts) of the system used to train the models. We use this information to compute the total power consumption of each setting, also reported in Table 4.

We can further estimate the CO² emissions in kilograms of each single model by multiplying the total power consumption by the average CO² emissions per kWh in our region, which were around 30g/kWh between the 30th of December when the models were trained. Thus the total CO² emissions in kg for one single model can be computed as:

\[
 CO_2e = 0.030p_t
\]

All emissions are also reported in Table 4.

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1. Nvidia Tesla V100 specification
2. Intel Xeon Gold 6248 specification
3. Intel Xeon Gold 6226 specification
4. Rte - eCO²mix