FQuAD: French Question Answering Dataset

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Abstract

Recent advances in the field of language modeling have improved state-of-the-art results on many Natural Language Processing tasks. Among them, the Machine Reading Comprehension task has made significant progress. However, most of the results are reported in English since labeled resources available in other languages, such as French, remain scarce. In the present work, we introduce the French Question Answering Dataset (FQuAD). FQuAD is French Native Reading Comprehension dataset that consists of 25,000+ questions on a set of Wikipedia articles. A baseline model is trained which achieves an F1 score of 88.0% and an exact match ratio of 77.9% on the test set. The dataset is made freely available at https://fquad.illuin.tech.

1 Introduction

Current progress in language modeling has led to increasingly successful results on various Natural Language Processing (NLP) such as Part of Speech Tagging (PoS), Named Entity Recognition (NER) and Natural Language Inference (NLI). Large amounts of unstructured text data, available for most of the languages, have facilitated the development of Language Models. Therefore, the releases of language specific models in Japanese, Chinese, German and Dutch[1], amongst other languages, are now thriving. In late 2019, two French language models, CamemBERT[2] and FlauBERT [3], were released.

On the other hand, task and language specific datasets are costly and difficult to collect. Consequently, the training of task specific models is mostly restricted to English or machine translated datasets due to a lack of quality annotated datasets. This can be observed in particular with the Reading Comprehension task where Question Answering models have made important progress over the past few years. Indeed, the available datasets such as SQuAD1.1[4], SQuAD2.0[5] or CoQA[6] are only available in English. While efforts have been carried out into translating datasets such as SQuAD1.1[4] to train multilingual models[7], those fail to reach English comparable results on other languages.

In order to fill the gap for the French language, we built a French Reading Comprehension dataset similar to SQuAD1.1. The dataset consists of over 25,000+ pairs of questions and answers, annotated by a team of university students. The present dataset is a first version that we hope will be extended in future releases. The dataset’s training, validation and test sets are respectively made up of 20731, 3188 and 2189 samples.

Furthermore, we trained a Question Answering model on the resulting dataset, leveraging the now popular transfer learning approach using pretrained Language Models during training. We restricted our experiments to the recently released French pretrained language models, i.e. CamemBERT and FlauBERT.

Our contribution sums as follows:

• FQuAD The first native French Question Answering Dataset, which includes 25,000+ question-answer pairs.

• CamembertQA The first French Question Answering model, based on CamemBERT and trained on FQuAD, reaching a state-of-the-art of 88.0% F1 score, and 77.9% EM.

2 Related Work

The Question Answering field is an active area of research with several distinct sub tasks. An overview of the various approaches underlying this task is detailed by Ruder. The Reading Comprehension task (RC) attempts to solve the Question Answering (QA) problem by finding the text span in one or several documents or paragraphs that answers a given question[8].

To our knowledge, this dataset is the first of its kind although ongoing efforts are being made on the same task at https://piaf.etalab.studio

Both contributions are freely available at https://fquad.illuin.tech.
2.1 Reading Comprehension in English

Many Reading Comprehension datasets have been built in English. SQuAD1.1 (Rajpurkar et al., 2016), then later SQuAD2.0 (Rajpurkar et al., 2018) has become one of the reference dataset for training question answering models. Later, similar initiatives such as NewsQA (Trischler et al., CoQA (Reddy et al., 2018), QuAC (Choi et al., 2018), HotpotQA (Yang et al., 2018) have broadened the research area for English Question Answering.

The datasets are similar but each of them introduce their own subtleties. For instance, SQuAD2.0[5] develops unanswerable adversarial questions. CoQA[6] focuses on Conversation Question Answering (CQA) in order to measure the ability of algorithms to understand a document and answer a series of interconnected questions that appear in a conversation. QuAC[10] focuses on Question Answering in Context developed for Information Seeking Dialog (ISD). The benchmark from Yatskar (2018) offers a qualitative comparison of these datasets. Finally, HotPotQA[11] attempts to extend the Reading Comprehension task to more complex reasoning by introducing Multi Hop Questions (MHQ) where the answer must be found among multiple documents.

2.2 Reading Comprehension in other languages

Different approaches can be imagined to extend Question Answering models to other languages:

1. Crowd-source a new language specific dataset and train a language specific model
2. Translate SQuAD with Neural Machine Translation (NMT) and train a language specific model.
3. Use NMT to translate both questions and contexts in English at inference time, and predict using an English QA model.
4. Use a multilingual language model, and train on either English or language specific dataset.

Native Question Answering  There are currently, to our knowledge, no available large-scale crowd-sourced datasets in languages other than English. Indeed, such annotated datasets are expensive to collect, making training Question Answering models in other languages challenging[7]. Note that however that Lewis et al. have made significant efforts to annotate QA tests sets for various languages, such as German, Spanish and Arabic.

Translated Question Answering Very recently, a large scale initiative in another language than English is reported by Carrino et al. (2019).

They develop a specific translation method called Translate-Align-Retrieve (TAR). Using the TAR method, they were able to build the SQuAD-es dataset that is the translation the majority of the available paragraph, context and answer samples. Then, they finetune a multilingual on the resulting dataset and reach a performance of respectively 68.1/48.3% F1/EM and 77.6/61.8% F1/EM on MLQA[7] and XQuAD[14].

Inference Translated Question Answering Following approach 3, Asai et al. in 2018 first developed a QA model for French and Japanese, reaching a 62.0 % F1 performance (40.7 % EM) in French, on a small hand-made test set of 327 questions. Research works on cross-lingual language representations in XQuAD (On the Cross-lingual Transferability of Monolingual Representations, Artetxe et al., 2019) also issued small question answering datasets in various languages. Lewis et al. (MLQA: Evaluating Cross-lingual Extractive Question Answering, 2019) enlarged these datasets to 7 languages on small test sets: English, Arabic, German, Spanish, Hindi, Vietnamese and Simplified Chinese.

Cross-lingual Question Answering On top of Asai et al. approach, Siblini et al. in 2019 used a multilingual BERT representing both French and English texts in the same space. This multilingual BERT was trained on English texts of SQuAD1.1, and evaluated on the small Asai et al. French corpus. This interesting setup reached a promising score of 76.7/61.8 % F1/EM.

The table 1 lists some of the available datasets along with the number of samples they contain. By means of comparison, Table 1 also includes FQuAD, whose collection is presented in the upcoming sections.

| Dataset          | Language | Size   |
|------------------|----------|--------|
| SQuAD1.1         | En       | 100k+  |
| SQuAD2.0         | En       | 150k+  |
| NewsQA           | En       | 100k+  |
| CoQA             | En       | 127k+  |
| QuAC             | En       | 98k+   |
| HotpotQA         | En       | 113k+  |
| SQuAD-es         | En       | 87595  |
| FQuAD            | Fr       | 25k+   |

Table 1: Benchmark of existing Reading Comprehension datasets, including FQuAD.

2.3 Language Modelling for Reading Comprehension

Increasingly efficient language models have been released over the past two years such as GPT-2

[3][https://nlpprogress.com/english/question_answering.html]
(Radford et al., 2018), BERT (Devlin et al., 2018) and XLNet (Yang et al., 2019). Indeed, they have disrupted Question Answering and most of NLP fields: pretraining a language model on a generic corpus, eventually fine-tuning it on a domain specific corpus and then training it on a downstream task is the de facto state-of-the-art approach for optimizing both performance and annotated data volumes.

Top performances on the SQuAD1.1 leaderboard are mainly variations around the XLNet and BERT models. On other languages, multilingual models have been released and pretrained, for instance XLM (Lample and Conneau, 2019), BERT Multilingual (Pires et al., 2019), or more recently XLM-R (Conneau et al., 2019).

Focusing on French language, CamemBERT (Martin et al., 2019) and FlauBERT (Le et al., 2019) language models recently enabled a complete new range of opportunities for French NLP applications. These very recent steps forward in French language modeling now provide all the tools needed for developing cutting-edge NLP applications in French. Details about both models are given in the following paragraphs.

**CamemBERT** The CamemBERT[2] language model is a RoBERTa[23] based model. The architecture of the model follows the BERT BASE configuration[18], i.e. 12 layers, 768 hidden dimensions, 12 attention heads. It was trained on the French part of the Oscar dataset[24]. More specifically, the amount of data used amounts to 138 GB of data and 32.7 billion of tokens[2], leading to 110M parameters. The vocabulary is built using the SentencePiece algorithm[25] with a size of 32k tokens. Note also that the model was not trained on the next sentence prediction task and does therefore not support the sentence embedding. It was evaluated on several downstream tasks such as Part-of-Speech tagging, Named Entity Recognition and Natural language inference. The model has not been evaluated yet on the Question Answering tasks as most of its English counterparts did on SQuAD1.1 and SQuAD2.0.

**FlauBERT** The FlauBERT[3] language model is a BERT based[18] language model. The model comes with two architectures. The FlauBERT$_{BASE}$ follows the same architecture as CamemBERT[2]. The FlauBERT$_{LARGE}$ architecture configuration is given by : 24 layers, 1024 hidden dimensions and 16 attention heads. The total number of parameters amounts respectively to 137M and 373M parameters. The training dataset consists of several sub-corpora that are gathered from various sources such as books and Wikipedia articles. The total dataset size for training the model amounts to 71 GB. The model has not been evaluated yet on the Question Answering tasks as most of its English counterparts did on SQuAD1.1 and SQuAD2.0.

### 3 Approach

First, we explore the opportunity to develop a native French Question Answering model. We chose on adopt the same approach as the one adopted by Rajpurkar et al. in the process of building SQuAD1.1. Indeed, while other Reading Comprehension datasets exists, many efforts have been carried out into translating SQuAD, such as in Spanish by Carrino et al. or into building native multilingual[7] test sets for other languages but not French.

Second, since no French Reading Comprehension dataset is currently available we translate SQuAD1.1 into French with the English-French NMT model (Ott et al., 2018). As it is still not clear how the translation process affects the performances on native datasets, we compare the results for both approaches. Translation based approaches face the challenging issue of aligning source and translated pieces of text, as the words order and quantity may change during translation. Although realignment difficulties deprived us from approximately half of the original dataset, 40,000 samples were still collected. Training an adapted CamemBERT (Martin et al.) model for QA on this translated SQuAD1.1. Results of this training are presented in the Experiments section.

Third, a French Question Answering model is trained by fine-tuning CamemBERT[2] and FlauBERT[2] on FQuAD and on the translated dataset.

### 4 Dataset Collection

The collection procedure for our dataset follows the same standard as SQuAD1.1. First, paragraphs among diverse articles are collected. Second, question and answer pairs are crowd-sourced on the collected paragraphs. Third, additional answers on the test set are collected.

#### 4.1 Paragraphs collection

A set of 1,769 articles were collected from the French Wikipedia page referencing quality articles. From this set, a total of 145 articles were randomly sampled. Among them, articles are randomly assigned to the training, development and test sets with respective number of articles 117, 18 and 10, i.e respectively 81%, 12% and 7%. The paragraphs that are at least 500 characters long are kept for each article similarly to SQuAD 1.1. This technique resulted in 4951 paragraphs for the training set, 768 paragraphs for the development set and 749 paragraphs for the test set.
paragraphs for the development set and 532 for the test set.

4.2 Question and answer pairs collection

A specific Questions and Answers annotation platform was developed to collect the question and answer pairs. A total of 18 college students were hired as crowd-workers, in collaboration with the Junior Enterprise of CentraleSupélec ⁶.

Figure 1: The interface used to collect the question/answers encourages workers to write difficult questions.

The guidelines for writing question-answer pairs for each paragraph were the same as for SQuAD1.1. First, the paragraph is presented to the student on the platform and the student reads it. Second, the student thinks of a question whose answer is a span of text within the context. Third, the student selects the smallest span in the paragraph which contains the answer. The process is then repeated until 3 to 5 questions are generated and correctly answered. The students were asked to spend on average 1 minute on each question and answer pair. This amounts to an average of 3-5 minutes per annotated paragraph. Final dataset metrics are shared in Table 2.

| Dataset | Articles | Paragraphs | Questions |
|---------|----------|------------|-----------|
| Train   | 117      | 4921       | 20731     |
| Validation | 18   | 768        | 3188      |
| Test    | 10       | 532        | 2189      |

Table 2: The number of articles, paragraphs and questions for each set of FQuAD

A complete annotated paragraph is displayed on figure 2.

4.3 Additional answers collection

In order to obtain a more robust test set and decrease the annotation bias, the test dataset is enriched with additional answers for each question. Indeed, several answers could be correct for a given question: for instance the question *Quand fut couronné Napoléon ?* would have several possible answers such as *mai 1804*, *en mai 1804* or *1804*. As all these answers are admissible, enriching the test set with several annotations for the same question, with different annotators, is a way to decrease annotation bias. Answers in our test set are therefore labeled independently by three different annotators. The additional answers are also useful to get an indication of the human performance on FQuAD. For each question of the test set, two additional answers have been collected. The crowd-workers were asked to spend on average 20 seconds for each question.

4.4 Adversarial samples

The present dataset does not contain adversarial samples as in SQuAD2.0 by Rajpurkar et al., 2018. However, this will hopefully be released in a future version of the dataset.

5 Dataset Analysis

To understand the diversity of the collected dataset we performed two keyword analyses. First, a mix of PoS-tagging and patterns is used to analyse the frequency of different kinds of answers (see Table 4).
Reasoning Example Frequency
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**Synonymy**
Question: Quel est le sujet principal du film ?
Context: Le sujet majeur du film est le conflit de Rick Blaine entre l’amour et la vertu : il doit choisir entre...
35.2 %

**World knowledge**
Question: Quand John Gould a-t-il décrit la nouvelle espèce d’oiseau ?
Context: E. c. albipennis décrite par John Gould en 1841, se rencontre dans le nord du Queensland, l’ouest du golfe de Carpentarie dans le Territoire du Nord et dans le nord de l’Australie-Occidentale.
11.1 %

**Syntactic variation**
Question: Combien d’auteurs ont parlé de la merveille du monde de Babylone ?
Context: Dès les premières campagnes de fouilles, on chercha la « merveille du monde » de Babylone : les Jardins suspensus décrits par cinq auteurs...
57.4 %

**Multiple sentence reasoning**
Question: Qu’est ce qui rend la situation de menace des cobs précaire ?
Context: En 1982, les chercheurs en concluent que le cob normand est victime de consanguinité, de dérive génétique et de la disparition de ses structures de coordination. L’âge avancé de ses éleveurs rend sa situation précaire.
17.6 %

Table 3: Question-answer relationships in 108 randomly selected samples from the FQuAD development set. In bold the elements needed for the corresponding reasoning, in italics the selected answer.

| Answer type             | Freq [%] | Example                                      |
|-------------------------|----------|----------------------------------------------|
| Common noun             | 21.7     | rencontres                                   |
| Person                  | 17.6     | John More                                    |
| Other proper nouns      | 12.6     | Grand Prix d’Italie                         |
| Location                | 10.7     | Normand                                     |
| Date                    | 10.1     | 1815                                         |
| Other numeric           | 13.4     | 1.65 m                                       |
| Verb                    | 5.2      | être dépoussiéré                             |
| Adjective               | 4.5      | méprisant, distant et sec                    |
| Other                   | 1.1      | gimmick                                      |

Table 4: Answer type frequency in FQuAD

| Question (que)          | Freq | Example                                      |
|-------------------------|------|----------------------------------------------|
| What (que)              | 47.2 | Quel pays parvient à ...                     |
| Who                     | 14.9 | Qui va se marier bientôt ?                   |
| When                   | 10.0 | Quand a eu lieu la ...                       |
| Where                  | 9.2  | Où est l’échantillon ...                    |
| How many               | 6.5  | Combien d’albums ...                        |
| How                    | 5.9  | Comment est le prix ...                     |
| What (quoi)            | 3.7  | De quoi est faite la ...                    |
| Why                    | 2.0  | Pourquoi l’assimile ...                     |
| Other                  | 0.6  | Donner un avantage de ...                   |

Table 5: Distribution of question keyword

Second, a keyword based approach is used to analyse the frequency of the corresponding questions (see Table 5).

5.1 Answer analysis
To analyse the collected answers, a combination of rule-based regular expressions and entity extraction using spaCy[27] are used. First, a set of regular expressions rules are applied to isolate dates and other numerical answers. Second, person and location entities are extracted using Named Entity Recognition. Third, rule based approach is adopted to extract the remaining proper nouns. Finally, the remaining answers are labeled into common noun, verb and adjective phrases, or other if no labels were found. Answer type distribution is shown on Table 4.

5.2 Question analysis
The second analysis aims at understanding the question types of the dataset. This analysis is rule-based only. Table 5 first demonstrates that the annotation process issued a wide range of question types, underlining the fact that What (que) represents almost half (47.0%) of the corpus. This important proportion may be explained by this formulation encompassing both the English What and Which, as well as a possible natural bias in the annotators way of asking questions. This bias may probably be the same at inference time, as it originates from native French structure.

5.3 Question-answer differences
The difficulty in finding the answer given a particular question lies in the linguistic variation between the two. This can come in different ways, which are listed in Table 3. The categories are taken from [4]: Synonymy implies key question words are changed to a synonym in the context; World knowledge implies key question words require world knowledge to find the correspondence in the context; Syntactic variation implies a difference in the structure between the question and the answer; Multiple sentence reasoning implies knowledge requirement from multiple sentences in order to answer the question. We randomly sampled 6 questions from each article in the development set and manually labeled them. Note that samples can belong to multiple categories.

6 Evaluation
6.1 Dataset
As there is currently not a native French evaluation dataset, the evaluation can only be carried out on English Datasets that are translated in French.
For this purpose the SQuAD training and development sets were translated by NMT. Note that the translation process makes it difficult to keep all the samples from the original dataset as the translated answers do not always align with the start/end positions of the translated paragraphs.

In the present work, those datasets will respectively be referred to as SQuAD-fr-train, SQuAD-fr-dev and contain respectively 40.7k+ and 5.7k+ data samples. The two versions of the translated development set of SQuAD can be used to evaluate the performances of the models and compare those to the FQuAD test set. The use of SQuAD-train-fr is two-fold; as a standalone training dataset or as augmentation data for FQuAD training set.

Note that a French translated dataset from Asai et al. could be used for the evaluation. However, the set contains only 327 translated samples from SQuAD1.1 development set an contains many redundant questions making it a poor baseline to evaluate to model.

6.2 Evaluation metrics

In order to evaluate the quality of the model, the Exact Match (EM) and F1-score metrics are computed. In SQuAD1.1, both the F1 and EM ignore English punctuation and the a, an, the articles. For the French evaluation process, consistently with SQuAD, the same approach is adopted and following articles are ignored: le, la, les, du, des, au, aux, un, une.

**Exact match (EM)** EM measures the percentage of predictions matching exactly one of the ground truth answers.

**F1 score** The F1 score is the average overlap between the predicted tokens and the ground truth answer. The prediction and ground truth are processed as bags of tokens. For questions labeled with multiple answers, the F1 score is the maximum F1 over all the ground truth answers.

6.3 Human performance

Similarly to SQuAD, human performance is evaluated in order to assess how humans can agree on answering questions. This score gives a comparison baseline when assessing the performance of a model. To measure the human performance, for each question, two of the three answers are considered as the ground truth, and the third as the prediction. In order not to bias this choice, the three answers are successively considered as the prediction, so that three human scores are calculated. The three runs are averaged to obtain the final human performance. F1 and EM score are computed based on this setup, yielding a human score of 92.1% F1 and 78.4% EM. By means of comparison, the reported human score for SQuAD1.1 is equal to 91.2% F1 and EM 82.3% EM.

7 Experiments

In the present section, the results of the experiments are presented. First, these experiments are carried out on the FQuAD and the french translated SQuAD1.1. They provided us insights about the differences in training models on native french or translated samples. Second, an analysis of the model predictions is carried out to understand its success rate per question and answer category. Third, a learning curve on the FQuAD training set is presented and discussed in view of future annotation opportunities. All experiments are carried out thanks to the BERT-based French Language Models recently released, CamemBERT[2] and FlauBERT[3], the process of training a French Question Answering model becomes straightforward using the implementation released by HuggingFace [28].

### 7.1 Results

The benchmark includes our training experiments of CamemBERT and FlauBERT on FQuAD, on SQuAD-train-fr, and on the combination of both. All models are evaluated on the FQuAD test set, and benchmarked on SQuAD-dev-fr and SQuAD-dev-fr-mt. Existing approaches from Asai et al. and Siblini et al., evaluated on SQuAD-dev-fr-mt, are
Table 8: Experiments and related work summary over different language models and training data. We compare the evaluations on FQuAD-test and SQuAD-dev-fr-
    Testing data
    | Model            | Training data | FQuAD-test |  |  | SQuAD-dev-fr |  |  |
    | Human Performance| -             |  |  |  |  |  |  |
    | CamemBERTQA      | FQuAD         |  |  |  |  |  |  |
    | CamemBERTQA      | SQuAD-fr-train|  |  |  |  |  |  |
    | CamemBERTQA      | FQuAD + SQuAD-fr-train |  |  |  |  |  |  |
    | FlauBERT_LARGE   | FQuAD         |  |  |  |  |  |  |

also included in the comparison. The results of the experiments are summed up in table 8.

First, our best model, CamemBERTQA, reaches a performance of 88.0% F1 and 77.9% EM on the FQuAD test dataset, which is the highest score across the experiments. By means of comparison, the head of the SQuAD1.1 leader-board (XLNet, Yang et al., 2019) reaches 95.1% F1 and 89.9% EM on the SQuAD1.1 test set. Interestingly, while the size of FQuAD remains four time smaller than its English counterpart, the CamemBERT + FQuAD approach issues a very promising baseline.

Second, CamemBERT is trained solely on the translated dataset SQuAD-train-fr. The translation was carried out using state-of-the-art NMT (Ott et al.). This approach yields a strong baseline that reaches 84.1% F1 and 70.9% EM. Compared to the previous model, this result is about 4 points less effective in terms of F1 score and even more important in terms of EM score, i.e. 7. This difference is probably explained by the fact that NMT produces translation inaccuracies that impact the EM score more than F1 score.

The third experiments attempts to augment the FQuAD training set by adding the translated samples of SQuAD-train-fr. The resulting model reaches a F1 and EM score of respectively 87.4% and 76.4%. Interestingly, those results are not outperforming the one of the first experiment despite the fact that the number of training samples have more than tripled. The reason is probably due to a low overall quality of translated question and answer pairs that brings additional noise and that might harm the learning process. Human annotated questions in French embed language specific subtleties that a NMT model cannot capture.

Finally, the FlauBERT Large pretrained french language model is fine-tuned on the FQuAD training dataset. The resulting model yields a performance of 80.6/70.3% F1/EM score. The present result is surprising as the original FlauBERT rivals or even surpasses CamemBERT performances on several downstream tasks (Le et al.) such as Text Classification, Natural Language Inference (NLI) or Paraphrasing. The difference with the first model may be explained by the difference in pretraining data volumes (138GB for CamemBERT, 71GB for FlauBERT).

7.2 Performance analysis

We ran some performance analysis on question and answer types, to understand the strengths and shortcomings of the trained model. Tables 6 and 7 present these analyses, sorted by F1 score. CamemBERTQA performs better on structured data such as Date, Numeric or Location. Similarly, the model performs well on questions seeking for structured information, such as How many, Where, When. EM top scores also highlight structured answer types such as Date and Location. More interestingly, Person and Adjective answer types are also top ranked on EM score, meaning that these answers are easier to detect exactly. Regarding the question types, When and Who questions lead to high EM scores, probably because the answers expected by these questions are short and easily identifiable within a text. On the other end, the How questions that probably expects a long and wordy answer are the least well addressed. Note that Verb answers EM scores are also quite low. This is probably due to either the variety of forms a verb can take, or to the fact that verbs are often part of long and wordy answers, which are by definition difficult to match exactly.

To improve the model on these drawbacks, future annotations should certainly include more of the less well-treated questions and answers.

Some prediction examples are available in the appendix. Selected samples are not part of FQuAD, but were taken from Wikipedia.

7.3 Learning curve

To further understand the model learning potential, we established the model learning curve. For each run an experiment is carried out on a subset of the FQuAD training using CamemBERT. The size of the subset is increased for each consequent run. Each resulting model is then evaluated on the FQuAD test set and the metrics (F1 and EM) are reported on the figure 3 with respect to the number
of samples involved in the training.

The figure 3 shows that both the F1 and EM score follow the same trend. First, the model is quickly improving upon the first 10k samples. Then, F1 and EM are progressively flattening upon augmenting the number of training samples. Finally, they reach a maximum value of respectively 87.98% and 77.87%. As the last 5k samples brought approximately 2.6 improvement on both F1 and EM, the performances are still expected to improve as more samples would be available.

By means of comparison, the target state-of-the-art level of SQuAD1.1 is 95/89.9% F1/EM. Assuming that SQuAD1.1 performances are transferable to French QA capabilities, further annotations should contribute strongly to reduce the gap between F1 and EM levels.

8 Discussion

The following section discusses various insights about the experiments. We mainly try to highlight the underlying bias between native and translated datasets, and between FQuAD and SQuAD1.1 paradigms.

8.1 Native or Translated French

**Native french** The top performance on the native French dataset (FQuAD-test) is reached when CamemBERT is trained only on native French (FQuAD-train). When adding some translated data to this training set, results do not seem to improve, despite the 40k+ additional samples. Therefore, the french translated data samples act here as noise with respect to native french, or at least do not carry more useful semantic information than the 20k+ FQuAD samples.

**Translated french** On the other hand, the top performance on the SQuAD-dev-fr dataset is reached when CamemBERT is trained on SQuAD-fr-train. When adding some native data to this training set, results don’t improve. Therefore, it seems here that Native French data acts here as noise towards translated data, or at least do not carry any more information than what’s included in the 40k+ samples of FQuAD-fr-train.

Furthermore, the top model CamemBERTQA trained on FQuAD performs worse on translated data, dropping to 70.7% F1 score. These insights show that there is a strong bias between translated and native French data. An interesting comparison basis lies into Carrino et al. research works. Their approach performs a 77.6/61.8% F1/EM score on a Spanish-translated SQuAD1.1, with a multilingual BERT. By means of comparison, CamemBERT reaches equivalent levels of performance when trained and evaluated on French-translated SQuAD1.1 (75.6/64.2% F1/EM). Although French and Spanish are different languages, they are close enough in their construction and structure, so that comparing these two approaches is relevant to us.

Given the level of effort put into Carrino et al. translation process, we could think that both translation-based approaches, although using very recent Language Models, appear to reach a performance ceiling with translated data. On our French side, this could mean that enriching training data with more translated texts is not likely to further improve the performances.

8.2 Comparison between FQuAD and SQuAD

CamemBERT trained on FQuAD + SQuAD-fr-train is quite robust to the change in evaluation sets. However, it still performs worse on SQuAD-dev-fr. As the training data includes both translated and native French QA pairs, this important difference in performance reflects a significant bias between FQuAD and SQuAD1.1 annotation paradigms. Different hypotheses to explain this variation are developed in the following paragraphs.

**Question and answer lengths** After comparing question and answer lengths between FQuAD and SQuAD1.1 train sets, we’ve determined that the length distributions are very close (Wasserstein distance of 2.31, resp. 1.83 characters), which excludes this hypothesis for the explanation.

**Answer types** Table 9 shows the answer type distribution in FQuAD. Comparing to SQuAD1.1, a significant difference exist on structured entities with +3.7% Date/Other Numeric answers and +8.3% of Person/Location/Other proper nouns information. Additionally, the fields on which
Table 9: Answer type comparison in FQuAD and SQuAD1.1

| Answer type    | FQuAD  | SQuAD (%) |
|----------------|--------|-----------|
| Common noun    | 24.7   | 31.8      |
| Person         | 17.6   | 31.9      |
| Other proper nouns | 12.6   | 15.3      |
| Location       | 10.7   | 4.4       |
| Date           | 10.1   | 8.9       |
| Other numeric  | 13.4   | 10.9      |
| Verb           | 5.2    | 5.3       |
| Adjective      | 4.5    | 3.9       |
| Other          | 1.1    | 2.0       |

FQuAD is unbalanced compared to SQuAD, as the ones on which CamemBERTQA performs best. This may explain part of the difference in performances. Further explorations are underway to explore more subtle insights such as the syntactic divergence.

To conclude, we tried to benchmark FQuAD and CamemBERTQA to existing QA approaches in French.

First, despite the quantity of annotated native French data, CamemBERTQA is still far from the English state-of-the-art performances reported on SQuAD1.1, mainly due to the major gap in dataset sizes.

Second, comparing FQuAD and translated versions of SQuAD1.1, we came to the conclusion that translated data carry limited information compared to native samples, therefore limiting the performance of QA models on native language when trained on translated data.

Finally, exploring the alleged bias between FQuAD and SQuAD1.1 annotation paradigms, we raised the hypothesis of a structural difference in current versions of these datasets. However, these differences might be explained by structural differences between French and English, partly due to fundamental differences between Latin and Anglo-Saxon languages. This hypothesis could be tested by evaluating CamemBERTQA on another language corpus, from the same Latin language family (e.g., Spanish, Italian). Also, this hypothesis could be verified with stricter annotation guidelines.

9 Conclusion

In the present work, we introduce the French Question Answering Dataset. To our knowledge, it is the first dataset for native French Reading Comprehension. FQuAD is collected from the set of high quality Wikipedia articles with the help of French college students. We obtained a state-of-the-art performance in French Question Answering by training the recently released French language model CamemBERT on FQuAD, obtaining a F1 score of 88.0 % and an exact match ratio (EM) of 77.9 %.

The FQuAD initiative is an ongoing process. Further steps are planned in order to enrich the current approach and dataset with new training samples, and strengthen development and test sets with new questions and multiple answers. FQuAD will be ultimately be extended with adversarial questions, as in SQuAD2.0. We have made our dataset freely available in order to encourage innovation in the French NLP area. Any complementary initiative to build a common native french Reading Comprehension dataset is welcome.

Finally, we quickly explored the opportunity to apply our model to various NLP applications such as parsing a text, extracting entities and relations, etc. These applications are currently processed through other NLP tasks such as Named Entity Recognition, Text Segmentation, or Natural Language Inference. Transferring the knowledge learnt in the Question Answering model to these applications offers a wide range of possibilities, and will be explored in the future.

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### A Example model predictions

**Article:** Brexit

**Paragraph:** La possibilité d’un second référendum sur la question du projet de sortie du Royaume-Uni de l’Union européenne avait peu de chance de se réaliser avec le Premier ministre Boris Johnson. Elle fut toutefois fréquemment évoquée dans la presse britannique et étrangère. « Un second référendum est la seule façon de clore le débat » du Brexit a affirmé au journal Le Monde Tony Blair. Le député britannique Dominic Grieve expulsé du Parti conservateur avec 21 autres collègues en septembre 2019 pour avoir voté contre Boris Johnson afin de bloquer une sortie sans accord, a affirmé dans un entretien à France 24 « que les Britanniques doivent connaître les conséquences d’un « no deal » et va plus loin en affirmant : « je ne suis pas optimiste sur le fait qu’il soit possible de trouver un accord que le Parlement veuille. La seule solution est un second référendum. »

**Question:** Quel événement a été longuement mentionné dans la presse étrangère ?
**Answer:** La possibilité d’un second référendum

**Question:** Combien de politiques ont été renvoyés du parti conservateur ?
**Answer:** 21

**Question:** Sur quoi porte le second référendum ?
**Answer:** projet de sortie du Royaume-Uni de l’Union européenne avait

**Question:** Quel journal a accordé une interview à Dominic Grieve ?
**Answer:** à France 24

**Question:** Quand Dominic Grieve a été renvoyé du parti conservateur ?
**Answer:** septembre 2019

**Article:** Rapport du GIEC

**Paragraph:** Le réchauffement planétaire atteindra les 1,5 °C entre 2030 et 2052 si la température continue d’augmenter à ce rythme. Le RS15 (rapport spécial sur le réchauffement climatique de 1,5 °C) résume, d’une part, les recherches existantes sur l’impact qu’un réchauffement de 1,5 °C aurait sur la planète et, d’autre part, les mesures nécessaires pour limiter ce réchauffement planétaire.

Même en supposant la mise en œuvre intégrale des mesures déterminées au niveau national soumises par les pays dans le cadre de l’Accord de Paris, les émissions nettes augmenteraient par rapport à 2010, entraînant un réchauffement d’environ 3 °C d’ici 2100, et davantage par la suite. En revanche, pour limiter le réchauffement au-dessous ou proche de 1,5 °C, il faudrait diminuer les émissions nettes d’environ 45 % d’ici 2030 et atteindre 0 % en 2050. Même pour limiter le réchauffement climatique à moins de 2 °C, les émissions de CO2 devraient diminuer de 25 % d’ici 2030 et de 100 % d’ici 2075.

Les scénarios qui permettraient une telle réduction d’ici 2050 ne permettraient de produire qu’environ 8 % de l’électricité mondiale par le gaz et 0 à 2 % par le charbon (à compenser par le captage et le stockage du dioxyde de carbone). Dans ces filières, les énergies renouvelables devraient fournir 70 à 85 % de l’électricité en 2050 et la part de l’énergie nucléaire est modélisée pour augmenter. Il suppose également que d’autres mesures soient prises simultanément : par exemple, les émissions autres que le CO2 (comme le méthane, le noir de carbone, le protoxyde d’azote) doivent être réduites de manière similaire, la demande énergétique reste inchangée, voire réduite de 30 % ou compensée par des méthodes sans précédentes d’élimination du dioxyde de carbone à mettre au point, tandis que de nouvelles politiques et recherches permettent d’améliorer l’efficacité de l’agriculture et de l’industrie.

**Question:** Quels sont les gaz à effet de serre autres que le CO2?
**Answer:** méthane, le noir de carbone, le protoxyde d’azote

**Question:** Quelles sont les conséquences d’un scénario limitant le réchauffement à 1,5 degrés ?
**Answer:** diminuer les émissions nettes d’environ 45 % d’ici 2030 et atteindre 0 % en 2050.

**Question:** Quelle part d’énergie doit être fournie par le renouvelable pour respecter l’accord ?
**Answer:** 70 à 85 %

**Question:** Quelle source d’énergie sera limitée à une production de 8 % si les émissions maximales sont respectées ?
**Answer:** gaz