Addressing Issues of Cross-Linguality in Open-Retrieval Question Answering Systems For Emergent Domains

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Abstract

Open-retrieval question answering systems are generally trained and tested on large datasets in well-established domains. However, lowresource settings such as new and emerging domains would especially benefit from reliable question answering systems. Furthermore, multilingual and cross-lingual resources in emergent domains are scarce, leading to few or no such systems. In this paper, we demonstrate a cross-lingual open-retrieval question answering system for the emergent domain of COVID-19. Our system adopts a corpus of scientific articles to ensure that retrieved documents are reliable. To address the scarcity of cross-lingual training data in emergent domains, we present a method utilizing automatic translation, alignment, and filtering to produce English-to-all datasets. We show that a deep semantic retriever greatly benefits from training on our English-to-all data and significantly outperforms a BM25 baseline in the cross-lingual setting. We illustrate the capabilities of our system with examples and release all code necessary to train and deploy such a system¹.

1 Introduction

One challenge of emergent domains is that the originating locality is unknown, leading to the need for reliable information to cross language barriers. However, it is unlikely that domain-specific information will be available across multiple languages for a new domain. Furthermore, information rapidly changes in emerging domains, compounding the challenge of accessing credible data.

An example of a prominent emergent domain is COVID-19, which has quickly spread across the globe. To combat the spread of misinformation about COVID-19, researchers have developed open-retrieval question answering (Chen and Yih, 2020) systems which use large collections of trusted documents. For example, Lee et al. (2020), Levy et al. (2021), and Esteva et al. (2021) all develop open-retrieval QA systems using large corpuses of scientific journal articles. However, because these systems focus on English, they leave a gap for implementation on emergent domains that do not originate in English-speaking locations.

To address the limitations of prior systems, we implement a cross-lingual open-retrieval question answering system that retrieves answers from a large collection of multilingual documents, where answers may be in a language different from the question (Asai et al., 2021).

In this work we take COVID-19 as an exemplar of an emergent domain and present our system, which addresses two main areas of importance:

- Cross-linguality: The locality of an emergent domain is unknown ahead of time, making cross-lingual QA essential. Additionally, because data can rapidly change in emerging domains, new information may develop in multiple languages, motivating the need for systems that work across many languages.
- *Scarcity of training data*: Data scarcity is an expected concern for emergent domains, but multilingual and cross-lingual data are even more limited. We demonstrate that by employing automatic translation, alignment, and filtering methods, this challenge can be overcome in low-resource open-retrieval QA.

This system demonstration provides in-depth technical descriptions of the individual components of our cross-lingual open-retrieval question answering system: cross-lingual retrieval and crosslingual reading comprehension modules. Then, we describe how to combine the components along with document re-ranking into the complete system, shown in Figure 1, and present several examples taken from our system.

¹Code is open-sourced on github (link). Short video demonstration provided on youtube (link).

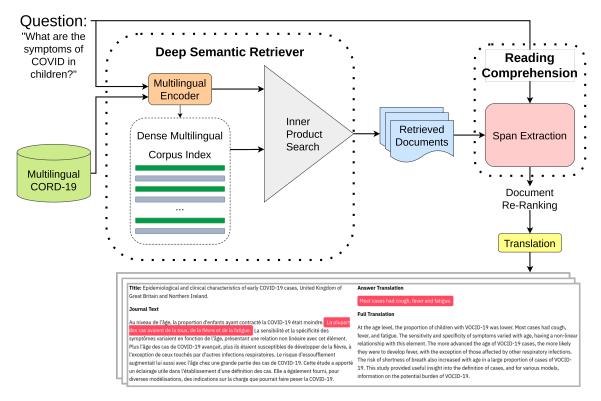


Figure 1: An overview of our cross-lingual COVID-19 open-retrieval question-answering system.

2 Cross-Lingual Dense Retrieval

Training a dense retriever is challenging in lowresource settings, such as emergent domains, due to the data-hungry nature of large language models. This challenge is compounded in the cross-lingual setting, where we aim to train a model to encode concepts from multiple languages into a similar location in the embedding space. In this section, we discuss how we overcome these challenges.

2.1 Data

Cross-lingual retrieval requires two datasets; a large-scale multilingual corpus of scientific articles from which to retrieve documents and a cross-lingual dataset for training the retriever. However, a very limited number of COVID-19 datasets have been released, few of which are multilingual and none of which are cross-lingual.

CORD-19 (Lu Wang et al., 2020) is a large-scale corpus of scientific papers on COVID-19, however a known limitation is that it contains only English articles. We draw inspiration from this work to address the lack of a large scale corpus of multilingual COVID-19 scientific articles. For our system, we use a manually collected corpus of English abstracts from PubMed, some of which have parallel abstracts in additional languages. The corpus is

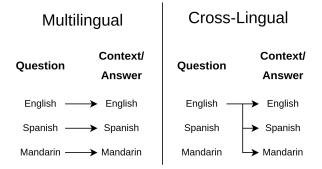


Figure 2: **Multilingual vs. cross-lingual question answering**: In the multilingual setting, QA pairs exist for multiple languages in a one-to-one mapping. On the other hand, in cross-lingual QA questions may have answers in any language, creating a one-to-many mapping.

collected using the same query as described by Lu Wang et al. (2020). We call this corpus multilingual CORD-19 (mCORD-19), and the language distribution can be found in Table 1.

To train our retriever we utilize the COUGH (Zhang et al., 2021) dataset, which is a multilingual FAQ retrieval dataset and consists of COVID-19 QA pairs. Although COUGH is multilingual, containing samples in 9 different languages, COUGH does not contain any cross-lingual QA pairs. The language distribution is shown in Table 1.

COUGH	9151 (en)	1077 (es)	778 (zh)	697 (fr)	573 (ja)	531 (ar)
mCORD-19	172977 (en)	1109 (es)	951 (zh)	711 (de)	614 (fr)	328 (pt)

Table 1: Top 6 languages by count for COUGH and the multilingual CORD-19 datasets. Language codes are the following: en-English, es-Spanish, zh-Chinese, fr-French, de-German, ja-Japanese, ar-Arabic, pt-Portuguese.

Answer Language	Spanish	Mandarin	French	Arabic	German	Russian	Vietnamese	Italian
En2All	8695	8441	8372	8231	8226	8156	8072	8003
Filtered En2All	6620	5869	5635	5808	5867	4137	531	6568

Table 2: QA pairs in our En2All and Filtered En2All variants of the COUGH dataset, where each question is in English, and the context and answer are in the language specified above.

2.2 Cross-lingual Data Generation

To address the lack of cross-lingual data in COUGH we introduce a modification of the dataset which we call English-to-all (En2All), where we convert the dataset from the multilingual to cross-lingual setting, as demonstrated in Figure 2. Because we are interested in a system which will find non-English answers to English questions, we create En2All through two translation processes. First, we translate the answer portion of every QA pair from COUGH into eight languages: Arabic, French, German, Italian, Mandarin, Russian, Spanish, and Vietnamese. Secondly, we translate the question portion of all QA pairs from any of the above languages into English².

As machine translation models do not perform perfectly, there may be instances within En2All that contain poor translations. To resolve this problem, we utilize LaBSE (Feng et al., 2020), an existing BERT-based sentence embedding model that encodes 109 languages into a shared embedding space. The model is utilized to compare the alignment of translations across different languages. We take the following steps to filter out any poor translations in the data:

- We step through the current En2All and calculate similarity scores between translated answers and their original English answers. To do this, we have eight different comparisons for each translated English QA pair.
- 2. Once the similarity scores have been calculated, we remove translations that do not meet a threshold and are classified as poor translations.

After going through these steps, roughly one-third of the data samples from En2All are removed for poor translations.

2.3 Methodology: Deep Semantic Retriever

Our retrieval model is based on the dense passage retriever from Karpukhin et al. (2020). In contrast to their work, we train a unified encoder that encodes both query and corpus into a shared space. For the encoder, we train the multilingual BERT (mBERT) (Devlin et al., 2019) and XLM-RoBERTa (XLM-R) (Conneau et al., 2020) Both models have been pre-trained models. using a tokenizer which shares a vocabulary for over 100 languages, allowing the models to encode all languages into a shared space. We train these models on the FAQ retrieval task by maximizing the inner product of correct QA pairs and minimizing the inner product of within-batch incorrect pairs.

2.4 Cross-Lingual Retrieval Evaluation

To evaluate our models in the large-scale openretrieval setting we utilize the questions from COUGH and En2All as our queries and the mCORD-19 dataset for our retrieval corpus. Because we have no ground truth labels for correct documents, and indeed there may be some unanswerable questions given this corpus, we measure model quality through a fuzzy matching metric, Fuzzy Match at top k documents (FM@k). FM@k utilizes the multilingual Sentence-BERT model from (Reimers and Gurevych, 2019)³. Each of the top k retrieved documents is split into it's component sentences and embedded using the sentence-BERT model. Next, each sentence is compared

²All translations are generated by the MarianNMT system (Junczys-Dowmunt et al., 2018) through the Huggingface Transformers (Wolf et al., 2020) library.

³We use the 'paraphrase-multilingual-mpnet-base-v2' variant

COUGH (FM@5/100)	COUGH +En2All (FM@5/100)
18.6	/41.4
22.8/49.5	26.4/50.7
28.0/54.9	27.7/51.7
25.0/51.3	28.1/51.6
30.1/55.4	28.4/52.2
32.9/56.7	30.9/53.4
30.5/56.6	29.8/53.2
32.1/56.4	29.6/52.9
	(FM@5/100) 18.6 22.8/49.5 28.0/54.9 25.0/51.3 30.1/55.4 32.9/56.7 30.5/56.6

Table 3: **Retrieval evaluation results**. All models are trained on COUGH and additional training data is denoted by "+". The middle column takes queries from COUGH, the right column from COUGH and En2All. For both columns, the retrieval corpus is mCORD. FM@5 and FM@100 are the fuzzy matching techniques proposed to determine open-retrieval accuracy described in section 2.4. Because BM25 is not cross-lingual, we translate it's queries into all languages in order to fairly compare against our cross-lingual models.

with the ground truth answer by calculating the cosine similarity with the reference answer embedding from COUGH. If any of the cosine similarities for that documents sentences are above a threshold, the document is evaluated as a positive retrieval.

The results for our models and a BM25 baseline⁴ are found in Table 3. Since a multilingual BM25 cannot perform cross-lingual retrieval, in order to fairly compare against cross-lingual models, we translate all queries into every other language in the mCORD corpus and then perform BM25 retrieval.

BM25 drastically underperforms compared to encoder models and demonstrates the need for a dense retrieval model. Although encoder models outperform BM25 when trained on multilingual data (COUGH), they are further improved by training on cross-lingual data (En2All). Additionally, after filtering low quality translations from En2All, we see further improvement in performance.

3 Cross-Lingual Reading Comprehension

3.1 Data

To train our cross-lingual reading comprehension model, we would ideally use a cross-lingual covidspecific question answering dataset. However, similarly to cross-lingual retrieval no such dataset exists so we augment existing datasets.

Model	MCQA	MCQA+En2All
Widdei	(EM/F1)	(EM/F1)
mBERT _{base}	20.0/57.5	19.6/55.4
+ XQuAD	21.2/57.7	20.5/55.6
+ En2All	19.3/56.1	19.2/55.8
XLM-R _{base}	25.1/60.0	24.4/58.9
+ XQuAD	26.7/61.6	26.1/61.3
+ En2All	24.0/58.8	23.9/58.3
XLM-R _{large}	26.5/ 62.7	26.4/ 62.2
+ XQuAD	29.1 /62.1	29.0 /61.7
+ En2All	26.3/61.1	26.6/60.8

Table 4: **Reading comprehension evaluation results**. All models are trained on MCQA, and additional training data is denoted by "+". The left column shows evaluation on a multilingual dataset where questions/contexts are always in the same language. The right column additionally evaluates on a cross-lingual dataset where questions are in english and context paragraphs may be in any language.

Artetxe et al. (2020) introduced XQuAD, a multilingual QA dataset composed of 240 paragraphs and 1190 QA pairs from SQuAD v1.1 which have been professionally translated into 10 languages. We utilize XQuAD as a pretraining dataset before performing any training on covid-specific datasets⁵. Möller et al. (2020) introduce Covid-QA, a covidspecific QA dataset consisting of 2019 questionanswer pairs, however, it contains english-only data. We modify Covid-QA with translations from MarianMT (Junczys-Dowmunt et al., 2018) to generate two dataset variants based on the multilingual and cross-lingual settings shown in Figure 2: Multilingual Covid-QA (MCQA) and English-toall (En2All). MCQA is a multilingual version of Covid-QA, created by translating all QA pairs into 9 languages to match those from XQuAD: Arabic, German, Greek, Spanish, Hindi, Mandarin, Romanian, Russian, and Vietnamese. En2All is our crosslingual variation of Covid-QA, in a similar spirit to the cross-lingual variant of COUGH. Because Covid-QA is english-only, to generate En2All we translate all contexts/answers into the same 9 languages as MCQA.

3.2 Methodology: Span Extraction

Similar to our dense semantic retriever, we train mBERT and XLM-RoBERTa models for our reading comprehension task. We formulate reading comprehension as a span extraction task, where each model learns to find start and end tokens which represent the answer span in a document.

⁴BM25 Implementation details found at https://github.com/alon-albalak/XOR-COVID/tree/master/bm25

⁵We open-source our models pretrained on XQuAD at https://huggingface.co/alon-albalak

Ask any question about COVID-19! Enter your question What are the symptoms of covid in children?	
Top Retrieved Articles	
2020-01-01	-
Title: SARS-CoV-2 infection in children.	Answer Translation
Journal Text	Fever, cough, sore throat, fatigue, nostril current, and more rarely vomiting and diarrhea.
İki bin on dokuz Aralık ayı itibariyle Çin'in Wuhan bölgesinden başlayarak, tüm dünyayı etkisi altına almış olan bir RNA virüsü olan SARS-CoV-2 tüm yaş gruplarını olduğu gibi çocukları da etkilemektedir. İki bin yirmi Mart ayı itibariyle ülkemizde de ilk olgular görülmeye başlanmıştır. Damlacık ve bu damlacıkların kontamine ettiği yüzeylerden temas yoluyla yayılan SARS-CoV-2, çocuklara genel olarak temaslı oldukları erişkinlerden bulaşmaktadır. Fekal-oral yayılım gibi diger bulaş yolları hakkında kanıtlanmış bir bilgi yoktur. Erişkinlere benzer şekilde çocukların ilk başvuru yakınmaları arasında <mark>ateş, öksürük, boğaz ağrısı, halsizlik, burun akıntısı ve daha nadiren kusma ve ishal</mark>	Full Translation As of December 2, 19, China's SARS-COV-2, an RNA virus that has influenced the entire world from the Wuhan region, has affected children as well as all age groups. As of March 2, 20th, the first phenomena began to be seen in our country as well. The droplet and the droplets are emitted through contact with the surfaces of SARS-COV-2, which are generally linked to children. There is no evidence of other infections, such as feal-oral emissions.
2021-04-16	+
2021-03-01	+

Figure 3: **The main interface of our system**. At the top is the search bar, where the current query is "What are the symptoms of covid in children?" Below the search bar are the three retrieved articles, ranked by relevance. In this example, the first retrieved document has been expanded to show the title and original text in Turkish, on the left. And on the right is the translation of the answer and the full document into English.

3.3 Cross-Lingual Reading Comprehension Evaluation

To evaluate our models in the reading comprehension task, we utilize the QA datasets described in Section 3.1. We evaluate our models based on exact match (EM) and F1 metrics by comparing the predicted answer spans with ground-truth answers.

The results for our models are found in Table 4. We train each of our models on MCQA and supplement it with data from XQuAD or En2All. Interestingly, we find that although En2All improved models in the retrieval setting, it only hurt model performance in QA. We also see that pretraining on XQuAD improves performance in all metrics for both base models, but leads to a slight decrease in F1 score for XLM-R_{large}. In our demo, we utilize XLM-R_{large} which was pretrained on XQuAD because it has only slightly worse F1 score, but significantly higher exact match compared to the next best model.

4 Cross-Lingual Open-Retrieval Question Answering

Our system is composed of the retrieval and reading comprehension modules described in sections 2 and 3. The full end-to-end system is shown in Figure 1. After the retriever has been trained, the mCORD-19 corpus is encoded and stored in the dense multilingual corpus index. When a question is posed to the system, the query is encoded, and a maximum inner product search is performed over the index to find documents most similar to the query. Answers are then extracted from the retrieved documents and the documents are re-ranked based on answer confidence from the span extraction model. Finally, the answer spans and full documents are translated into English and presented to the user with highlighted answers.

5 Demo

The demonstration retrieves documents from our mCORD-19 corpus, which has been encoded by the deep semantic retriever from section 2.3. We provide examples from the demo in Figures 4, 5, and 6.

5.1 Sidebar Interface

Our system has an options sidebar, shown in Figure 7, which gives the user several choices before entering a query. The user can determine how many documents they would like to see results from, they can select which languages the retrieved documents should be in, and they can specify a date range for the publications to search over. If there are no relevant documents in the desired date range, then the system will retrieve from any date range and displays a message to inform the user.

Top Retrieved Articles	
2020-01-01	-
Title: SARS-CoV-2 infection in children.	Answer Translation
Journal Text	Fever, cough, sore throat, fatigue, nostril current, and more rarely vomiting and diarrhea.
İki bin on dokuz Aralık ayı itibariyle Çin'in Wuhan bölgesinden başlayarak, tüm dünyayı etkisi altına almış olan bir RNA virüsü olan SARS-CoV-2	Full Translation
tüm yaş gruplanın olduğu gibi çocukları de ekilemektedir. İlu bin yimir Mart ayı İtbaryle ülkemizde de ilk olgular görülmeye başlanımşıtır. Damlacık ve bu damlacıkların kontanını ettiği yüzyerlene temsə yoluya yayılan ASRS-Co-V-2, ocuklara genei olarak temsalı oldukları erişkinlerden bulaşmaktadır. Fekal-calı yayılım gibi diğer bulaş yollan hakkında kanıtlanmış bir bilgi yoktur. Erişkinlere benzer şekilde çocukların ilk başıvıru yakınmalan arasında <mark>ınteş, olkürüle, böğü ağırışı halisidik, burun akıntsı ve daha nadıren kuran ve ishas</mark> bulunmaktadır.	As of December 2, 19, China's SARS-COV-2, an RNA virus that has influenced the entire world from the Wuhan region, has affected children as well as all age groups. As of March 2, 20th, the first phenomena began to be seen in our country as well. The droplet and the droplets are emitted through contact with the surfaces of SARS-COV-2, which are generally linked to children. There is no evidence of other infections, such as feat-onal emissions.
2021-03-01	-
Title: Epidemiological and clinical characteristics of early COVID-19 cases, United Kingdom of Great Britain and Northern Ireland.	Answer Translation
Journal Text	Most cases had cough, fever and fatigue.
Au niveau de l'âge, la proportion d'enfants avant contracté la COVID-19 était moindre. La plupart des cas avaient de la toux, de la fièvre et de la	Full Translation
inform La sensibilité et la specificité des symptômes variaient en fonction de l'âge, présentant une relation non linéaire avec cet édirement. Plus L'âge des cas de COVID-19 avancier, luis li étaines susceptibles de développer de la hitiva, à l'exection de caux touches par d'autres infections respiratoires. Le risque d'essoufflement augmentait lui aussi avec l'âge chez une grande partie des cas de COVID-19. Cette étude a apporté un éclairage utile dans l'établissement d'une définition des cas. Elle a également fourni, pour diverses modélisations, des indications sur la charge que pourrait faire peser la COVID-19.	At the age level, the proportion of children with VOCID-19 was lower. Most cases had cough, lever, and fatigue. The sensitivity and specificity of symptoms varied with age, having a non-linear relationship with this element. The more advanced the age of VOCID-19 cases, the more likely they were to develop fever, with the exception of those affected by other respiratory infections. The risk of shortness of breath also increased with age in a large proportion of cases of VOCID-19. This study provided useful insight into the definition of cases, and for various models, information on the potential burden of VOCID-19.
2020-01-01	-
Title: Smell impairment in COVID-19 patients: mechanisms and clinical significance.	Answer Translation
Journal Text	Some of the patients with the SARS-CoV-2 virus identified have neurological symptoms.
Результаты многочисленных исследований показывают, что потеря обоняния — серьезный симптом, требующий тщательной	Most of them are not specific.
дифференциальной диагностики. Имеются убедительные данные, свидетельствующие о том, что нарушение обоняния не столько является признаком патологии полости носа и околоносовых пазух, сколько может оказаться проявлением нейродегенеративных	Headache, dizziness, fatigue, mialgia.
заболеваний. У части пациентов с выявленным вирусом SARS-CoV-2 наблюдаются неврологические симптомы. Большинство из них на на на на на на на на на на на на на	Full Translation
пациентов на фоне инфекции COVID-19 выявлены судороги, нарушение сознания, а также обнаружено наличие PHK 2019-NCoV в спинномозговой жидкости. Приводятся данные о развитии новых симптомов заболевания, в виде аносмии и дисгевзии.	The results of numerous studies show that loss of smell is a serious symptom requiring careful differential diagnosis. There is strong evidence that odor impairment is not o much a sign of nasal pathology and darnhea as It can be a manifestation of neurodegenerative disease. Some patients with the detected SAR5-CoV-2 Virus have neurological symptoms. Note of them are not specific — headschee, dizzines, fatigue, mialgia. A small percentage of patients with a COVID-19 infection show convulsions, consciousness impairments, and RNA 2019-NCOV in spinal fluid. Data on the development of new symptoms of the disease, in the form of anosmia and dysgesia, are given.

Figure 4: The top 3 non-English results for the query "What are the symptoms of covid in children?"

Top Retrieved Articles			
2021-02-01			
Title: Diabetes mellitus in old age.	Answer Translation		
Journal Text	According to Robert Koch Institute (RKI), diabetes patients are at risk for a severe course of "coronavirus disease 2019"		
Bei der Diabetestherapie im hohen Lebensalter müssen kognitive, funktionelle und konstitutionelle Ressourcen des Einzelnen beachtet werden. Rein	high blood pressure, oncological underlying disease, cerebrovascular and coronary heart disease.		
Hämoglobin(Hb)A 1c -orientierte Therapieziele treten in den Hintergrund. Vorrangig sollte Symptomfreiheit unter Vermeidung von Hypoglykämien und Erhalt der Lebensqualität angestrebt werden. Das geriatrische Assessment hilft, den aktuellen funktionellen, psychischen und kognitiven Zustand sowie den Förderungsbedarf	Full Translation		
bei multimotiden ätteren Mensionen zu kären und entiprochende simonite Therapiestrategien Instuduegen. Bei der medikamentiken Dukkesterangen im hohen Lebenalter müssen inbesondere Nereninsuftikenz und Exakösie sowie langsame Dosiangasungen beachter werden. Dukkesterangen im hohen Dukkesterangen inbesondere Nereninsuftikenz und Exakösie sowie langsame Dosiangenzugen beachter werden. Dukkesterangen inbesondere Bekönden inbesondere Nereninsuftikenz und Exakösie sowie langsame Dosiangenzos eine Bekönden dukkesteren gekönnt her Exakösie Gründenzen eine Statisteren eine Konstantister inderekonstantister dassenzen 2025 (COVID-1-9); weitere Reisofastoren dafür sind <mark>Exakösisteren eine Konstantisteren </mark>	In high-age diabetes therapy, cognitive, functional and constitutional resources of the individual must be taken into account. Purely hemoglobin (Hb) A Le-oriented therapy gala come into the baceground. Primarky, symptom-freeness should be sought while working they hopolycemia and maintaining the quality of the Gerantic assessment heips called up the current thurson, mental and cognitive condition as well as the need for support, the maintoined died they toge and to define approprinte therapeutic strategies. In high-age diabetes therapy, especially real insufficiency and excloses as well as slow dose adjustments must be taken into account. Diabetes primes below, according to Robert Koh Initiate (RK), the risk gives for a sever course of coronavirus disease 2019" (COVID-19); other risk factors for this are high blood pressure, oncological underlying disease, cerebrovascular and coronary heurt disease.		
2020-12-02	-		
Title: Healthcare challenges for people with diabetes during the national state of emergency due to COVID-19 in Lima, Peru: primary healthcare recommendations.	Answer Translation		
Journal Text	continuity of care involving contact with health facilities,		
Las personas con diabetes mellitus tipo 2 infectadas por SARS-CoV-2 tienen mayores riesgos de desarrollar COVID-19 con complicaciones y de morir como	must have regular access to medicines, tests and appointments with health personnel.		
consecuencia de ella. La diabetes es una condición crónica en la que se requiere continuidad de cuidados que implican un contacto con los establecimientos de salud, pues deben tener acceso regular a medicamentos, exámenes y citas con personal de salud. Esta continuidad de cuidados se ha visto afectada en el Perú a	Full Translation		
Des per versiteres nacesos regular interventinos, cominenta y tans competentes fastas. Con cominuous de cualados ser in estos encounses interventas interventas entrates en las competencias entrates en las competencias entrates en las competencias entrates en las competencias entrates entrates en las competencias entrates entrates en las competencias entrates	People with hyse 2 diabetes melitus intected with SARS-CoV-2 have a greater risk of developing COVID-19 with complications and of dying as a result of it. Diabetes is a chonic condition that requires continuity of care that involves contact with health Acilites, as they must have regular access to medicine, tests and appointments with them personnel. This control with oppoint and the access to the state of national emergency, product of the pandemic by COVID-19 as many health Acilities have supencide external constantiations. This article describes some strategies that have been developed by the different Pervanis health providers in the transmosk of the pandemic to provide continuity of care to poople with diabetes and fully provides recommendations for them to receive the care they need through the strengthening of the first level of care, as the closest point of contact with people with diabetes.		
2021-04-23	-		
Title: Severe diabetic ketoacidosis precipitated by COVID-19 in pediatric patients: Two case reports.	Answer Translation		
Journal Text	On the one hand, diabetes mellitus is associated with an increased risk of severe COVID-19.		
La relación entre la enfermediad por el coconavinos de 2019 (COVID-19) secundaria a SARS-CoV-2 y la diabetes mellitus se bidireccional. Para de la social associa manuella de COVID-19 associal de la construcción de la cons	diabetic ketoacidosis and severe metabolic complications of this presentation.		
	Full Translation		
	The relationship between coronavins disease of 2019 (20/DL-9) secondary to \$5485-60-2 and diabetes mellitus is toe-way (on the core hand, diabetes is associated with an increased disk of user COVD-19. On the OCDU-19. ON th		

Figure 5: The top 3 non-english results for the query "What are the concerns of having covid and diabetes?"

Ask any question about COVID-19!	
Enter your question	
What is the death rate of COVID?	
Top Retrieved Articles	
2021-01-01 Title: Disease severity classification and COVID-19 outcomes, Republic of Korea.	- Answer Translation
Journal Text	(1.6 per cent;
Показатели летальности были выше в городе Тэгу и провинции Кёнсан-Пукто (1.6%; 124/7756), чем в остальной части страны (0.5%; 7/1485). С 25 февраля по 26 марта 2020 года соотношение изоляторов с отрицательным Давлением на пациента с COVID-19 было ниже показателя в 0,15 в городе Тэгу и провинции Кёнсан-Пукто. В остальной части страны показатель указанного соотношения за тот же период снизился с 5,56 до 0,63. До введения в действие системы классификации 8 случаев смерти (15,7%) из 51 происходили дома или во время транспортировки пациентов из их домов в медицинские учреждения. Классификация пациентов по степени тяжести заболевания должна стать приоритетной мерой для облегчения нагрузки на систему здравоохранения и снижения показателей летальности.	(0.5 per cent; (15.7 per cent) Full Translation The death rate was higher in Tegu and Kyongsan Pukto Province (1.6 per cent; 124/7756) than in the rest of the country (0.5 per cent; 7/1485). From 25 February to 26 March 2020, the ratio of facilities with negative pressure on patients with COVID-19 was lower than 0.15 in Tegu and Kyongsan Pukto Province. In the rest of the country, the ratio fell from 5.56 to 0.63. Prior to the introduction of the classification system, 8 deaths (15.7 per cent) of 51 cases occurred at home or during the transport of patients from their homes to health facilities. The classification of patients by severity of the disease should be a priority measure to alleviate the burden on the health system and reduce the number of deaths.

Figure 6: A retrieved document for the query "What is the death rate of COVID", which shows multiple correct answers corresponding to different provinces of South Korea.

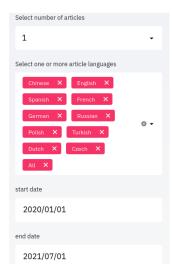


Figure 7: The options sidebar for our demonstration system. The options include: number of articles to return, article languages to retrieve from, and publication date range. For visualization purposes we show all language options.

5.2 Main Interface

To query the system, a user simply selects the desired options from the sidebar and enters their question into the search bar, as seen in Figure 3. After the user enters their question, the system will encode the question using the trained deep semantic retriever and find the most relevant documents within the given language and date range constraints. Then, the reading comprehension model will extract the answer (or answers) most relevant to the query from each retrieved document. Additionally, for any non-English documents, the system translates both the retrieved article and extracted answers into English⁶. Finally, the retrieved documents will be re-ranked based on the confidence scores for the extracted answers.

The desired number of documents will be displayed to the user as a list of publication dates. Each item can be expanded to show the article title, original document with highlighted answers, translated answers, and the full article translation. If an article contains a single answer, it will be highlighted in red. If there are multiple answers, each answer will be highlighted with a different color to allow for easy alignment between original answers and their translations, demonstrated in Figure 6.

6 Conclusion

In this work, we tackled two challenging areas in open-retrieval QA: cross-linguality and data scarcity. We presented methods for generating cross-lingual data in an emergent domain, COVID-19. Then, we demonstrated that an open-retrieval QA system trained on our data significantly outperforms a BM25 baseline. We hope that the methods presented here allow for increased access to reliable information in future emergent domains.

⁶All translations are generated by MarianNMT (Junczys-Dowmunt et al., 2018) from the Huggingface Transformers library (Wolf et al., 2020).

7 Broader Impact and Limitations

Crucial to any open-retrieval question-answering system, the **credibility and truthfulness of the documents is paramount**, in particular when trying to prevent and combat misinformation that arises in emergent domains. Any question-answering system is limited by the corpus used. To this end, we do our best to ensure that any information included in our corpus is truthful by including only peer-reviewed scientific articles from PubMed⁷.

Furthermore, there may be emergent domains without peer-reviewed scientific articles from which to draw answers. In these cases (and in fact in cases where peer-review does exist) it is imperative to include sources along with answers. This allows for users to judge the quality of information. In our system we present the title and date of publication for each returned article so that users can find the source content if desired.

Finally, **a known limitation** of dense-indexed open-retrieval systems is the static nature of the underlying database. This is a particularly important point for emerging domains, where current knowledge is quickly being updated. One disadvantage to the dense-index approach is that as new documents become available, the index may need to be recalculated if the new documents come from a significantly different distribution than the existing documents in the index. See here for further discussion and how to overcome these limitations.

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⁷https://pubmed.ncbi.nlm.nih.gov/

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A Additional Examples

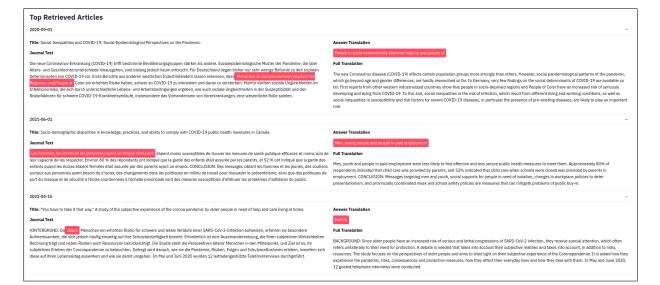


Figure 8: The top-3 non-english results for the query "Who is most vulnerable to covid?"