

A System for Worldwide COVID-19 Information Aggregation

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Abstract

The global pandemic of COVID-19 has made the public pay close attention to related news, covering various domains, such as sanitation, treatment, and effects on education. Meanwhile, the COVID-19 condition is very different among the countries (e.g., policies and development of the epidemic), and thus citizens would be interested in news in foreign countries. We build a system for worldwide COVID-19 information aggregation¹ containing reliable articles from 10 regions in 7 languages sorted by topics for Japanese citizens. Our reliable COVID-19 related website dataset collected through crowdsourcing ensures the quality of the articles. A neural machine translation module translates articles in other languages into Japanese. A BERT-based topic-classifier trained on an article-topic pair dataset helps users find their interested information efficiently by putting articles into different categories.

1 Introduction

Due to the global COVID-19 epidemic and the rapid changes in the epidemic, citizens are highly interested in learning about the latest news, which covers various domains, including directly related news such as treatment and sanitation policies and also side effects on education, economy, and so on. Meanwhile, citizens would pay extra attention to global related news now, not only because the planet has been brought together by the pandemic, but also because they can learn from the news of other countries to obtain first-hand news. For example, the epidemic outbreak in Korea is one month earlier than in Japan. Japanese citizens could prepare better for the epidemic if they had obtained more information from Korea. Citizens could learn from Asian countries about the

¹The authors are in alphabetical order.

¹Site: <http://lotus.kuee.kyoto-u.ac.jp/NLPforCOVID-19>

efficiency of masks before local official guidance. Universities can learn about how to arrange virtual courses from the experience of other countries. Thus, a citizen-friendly international news system with topic detection would be helpful.

There are three challenges for building such a system compared with systems focusing on one language and one topic (Dong et al., 2020; Thorlund et al., 2020):

- The reliability of news sources.
- Translation quality to the local language.
- Topic classification for efficient searching.

The interface and the construction process of the worldwide COVID-19 information aggregation system are shown in Figure 1. We first construct a robust multilingual reliable website collection solver via crowdsourcing with native workers for collecting reliable websites. We crawl news articles base on them and filter out the irrelevant. A high-quality machine translation system is then exploited to translate the articles into the local language (i.e., Japanese). The translated news are grouped into their corresponding topics by a BERT-based topic classifier. Our classifier achieves 0.84 F-score when classifying whether an article is about COVID-19 and substantially outperforms the keyword-based model by a large margin. In the end, all the translated and topic labeled news is demonstrated via a user-friendly web interface.

2 Methodology

We present the pipeline for building the worldwide COVID-19 information aggregation system, focusing on the three solutions to the challenges.

2.1 Reliable Website Collection

To avoid rumors and obtain high-quality, reliable information, it is essential to limit the information

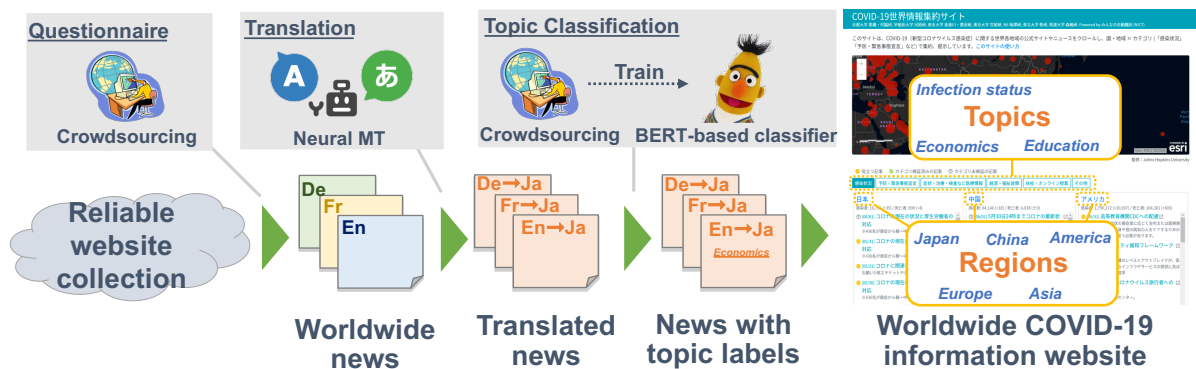


Figure 1: The construction process and the interface of the system.

Website	Country	Primary	Reason	Topics
www.cdc.gov	US	True	The site is a government website, specifically the Center for Disease Control.	infection status prevention and emergency declaration symptoms, medical treatment and tests
www.covid19-yamanaka.com	Japan	False	Shinya Yamanaka is a famous medical researcher and his insights about COVID-19 are reliable.	prevention and emergency declaration
www.internazionale.it	Italy	False	This website collects and translates articles from news agencies and magazines from all over the world. Has up-to-date news, but also long-form analysis articles. Most of my deeper information comes from here.	infection status economics and welfare prevention and emergency declaration school and online classes
covid.saude.gov.br	Brazil	True	This site is the government web site.	infection status

Table 1: Crowdworkers give trusted websites that they use to obtain COVID-19 related information. They also give the reasons to choose the website and what kind of information he/she obtains from the website.

sources. Since we aim to create a multilingual system, the first challenge is to obtain a list of reliable information providers from different countries and in different languages.

Crowdsourcing is known to be efficient in creating high-quality datasets (Behnke et al., 2018). To collect the list of reliable websites of a specific country, we use multiple crowdsourcing services (e.g., Crowd4U², Amazon Mechanical Turk³, Yahoo! Crowdsourcing⁴, Tencent wenjuan⁵) and limit the workers’ nationality because we assume that local citizens of each country know the reliable websites in their country. The workers not only suggest websites they think are reliable but they must also justify their choices and give a list of related topics they address, similar to constructing support for rumor detection (Gorrell et al., 2019; Derczynski et al., 2017).

We decided to use eight countries of interest, including India, the United States, Italy, Japan, Spain, France, Germany, and Brazil. For other countries or regions such as China and Korea, reliable web-

sites are provided by international students from these areas.

We treat official news from the governments as primary information sources and reliable newspapers as secondary information sources. We counted how many times each website was mentioned by the crowdworkers and found that the primary information sources tend to be ranked at the top three in each country. So we mainly crawl articles from primary sources.

Table 1 shows examples of the crowdsourcing results. The workers provide websites indicating for each one whether it is a primary or a secondary source, what are the reasons to choose this particular website, and which topics are addressed by the website. These topics are selected from a list that includes eight topics (e.g., *Infection status*, *Economics and welfare*, *School and online classes*).

2.2 Crawl, Filter and Translation for Information Localization

We crawl articles from 35 most reliable websites everyday by accessing the entry page and jumping to urls inside it recursively.

The number of crawled web pages is too big and exceeds the translation capacity. We consider only

²<https://crowd4u.org/>

³<https://www.mturk.com/>

⁴<https://crowdsourcing.yahoo.co.jp>

⁵<https://wj.qq.com>

the most relevant pages by filtering using keywords such as *COVID*. We can focus on pages with a higher probability to be COVID-19 related.

We use neural machine translation model TexTra⁶ with self-attention mechanism (Bahdanau et al., 2015; Vaswani et al., 2017). The translation system provides high-quality translation from news articles in multiple languages into articles in Japanese. The translation capacity is approximately 1,000 articles per day.

2.3 Topic Classification

To perform topic classification, we first collect the dataset via crowdsourcing. The topic labels are annotated to a subset of articles. Then we train a topic-classification model to label further articles automatically.

2.3.1 Crowdsourcing Annotation for Topic Classification

All articles are in Japanese after the translation stage, we then apply crowdsourcing annotation to label the articles with topics. As shown in Figure 2, the crowdsourcing workers first check the content of the page and give four labels to the article: whether it is related to COVID-19, whether it is helpful, whether the translated Japanese is fluent, and topics of the article.

Each article is assigned to 10 crowdworkers from Yahoo Crowdsourcing and we set a threshold to 50% for each binary question, i.e., if more than 5 workers think the article is related to COVID-19, then we label the article as *related*. We post this crowdsourcing task twice a week and can obtain 20K article-topic pairs each time.

2.3.2 Automatic Topic Classifier

The pretrained language model BERT (Devlin et al., 2019) shows reliable performance on many NLP tasks with limited annotated data including document classification (Adhikari et al., 2019; Sun et al., 2019). We use a pretrained BERT model in a feature based manner (Lee et al., 2019) where encoder weights kept frozen and train a classifier using the labeled articles by crowdsourcing. The BERT-based topic classification can then label other pages.

We also compare it with a keyword-based baseline method where we set keywords for each topic and find exact match.

⁶<https://mt-auto-minhon-mlt.ucri.jgn-x.jp/>

Figure 2: A sample of crowdsourcing annotation.

Country	#	Questionnaire	Reliable sites
India		122	67
US		106	77
Italy		104	68
Japan		102	49
Spain		126	90
France		127	71
Germany		106	61
Brazil		115	67
Total		908	550

Table 2: Statistics of the number of questionnaires and reliable sites of each country.

Country	Article with topic label
France	72K
America	11K
Japan	9K
China	10K
International	13K
Spain	1K
India	4K
Germany	2K
Total	122K

Table 3: Statistics of the article-topic dataset constructed by crowdsourcing.

3 Results

We show the topic classification result and statistical information of the interface in this section.

Task	Keyword-based model			BERT-based model		
	Precision	Recall	F-score	Precision	Recall	F-score
Is about COVID-19	0.36	1.00	0.54	0.82	0.87	0.84
Topic: Infection status	0.09	0.53	0.16	0.43	0.81	0.56
Topic: Prevention	0.05	0.73	0.10	0.19	0.73	0.30
Topic: Medical information	0.17	0.70	0.27	0.27	0.91	0.41
Topic: Economic	0.06	0.36	0.10	0.14	0.84	0.24
Topic: Education	0.06	1.00	0.11	0.05	0.60	0.09
Topic: Art and Sport	0.06	0.41	0.10	0.08	0.94	0.14
Topic: Others	0.52	0.07	0.13	0.87	0.79	0.83

Table 4: Topic classification results. Each line stands for one task. We use F-score to evaluate.

Country	Raw(↑/day)	Translated	With topics
France	774K(8K)	74K	9K
US	69K(730)	15K	2K
Japan	25K(260)	5K	2K
Europe	50K(510)	2K	50
China	38K(400)	3K	342
Int.	45K(470)	3K	263
Korea	16K(170)	260	71
Spain	4K(40)	370	36
India	14K(150)	860	66
Germany	16K(170)	8K	6K
Total	1.05M(11K)	110K	18K

Table 5: Statistics of the growing database of the system.

3.1 Reliable Website Collection

As shown in Table 2, we totally recieved 908 questionnaire results from 8 countries with totally 550 websites. Rumors are rampant in this era, the reliable websites dataset can help people to protect themselves from COVID-19 and avoid trusting rumors about COVID-19.

3.2 Topic Classification

We compared the BERT-based model with the keyword-based baseline model on topic classification task.

For the keyword-based method, there are totally 76 selected keywords of different topics such as *COVID*, *Remote work*, and *Social distance*.

For the BERT-based method, we use the pre-trained BERT-LARGE model with Whole Word

Masking (WWM) ⁷. We add one linear layer after the BERT encoder without fine-tuning the encoder. For every article, we take the hidden state of the ending symbol of each sentence as the sentence embedding and perform mean and max pooling of all sentence embeddings. The input of the linear layer is the concatenation of mean and max pooling embeddings and the output is a binary label. We randomly select 90% data from labeled data by crowdsourcing shown in Table 3 as a train set and remaining 10% as a test set.

As shown in Table 4, the BERT-based model outperforms the baseline model in almost all tasks. We can see that our system can reliably classify which articles are related to COVID-19, and that our interface can show related news to our users. Meanwhile, for some topic such as Arts & Sports and Education, the performance of the current system is still limited, which could be improved in future work.

3.3 Statistics of the System

The detail of the system database is shown in Table 5. There are totally 1.05M website pages with 110K of them translated into Japanese and 18K of them with topic labels. The dataset is still growing approximately 11K pages per day.

4 Conclusion

We built a system for worldwide COVID-19 information aggregation by combining crowdsourcing, crawling, machine translation, and a BERT-based topic classifier, which provides reliable, comprehensive and latest information from the world.

⁷<http://nlp.ist.i.kyoto-u.ac.jp/>

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Worldwide COVID-19 Information Aggregation Site

COVID-19世界情報集約サイト

京都大学 黒橋・村脇研, 早稲田大学 河原研, 東京大学 喜連川・豊田研, 東京大学 宮尾研, NII 相澤研, 東北大学 乾研, 筑波大学 森嶋研. Powered by みんなの自動翻訳 (NICT).

このサイトは、COVID-19（新型コロナウイルス感染症）に関する世界各地の公式サイトやニュースをクローリングし、国・地域 × カテゴリ（「感染状況」「予防・緊急事態宣言」など）で集約、提示しています。このサイトの使い方



提供：Johns Hopkins University

🟢 役立つ記事 🟢 カテゴリ検証済みの記事 🟡 カテゴリ未検証の記事

[日本](#) [中国](#) [アメリカ](#) [ヨーロッパ](#) [アジア\(日本・中国を除く\)](#) [その他国際](#)
 Japan China America Europe Asian (besides Japan and China) International

ヨーロッパ: 感染者: 1,189,445 (+3,403) / 死亡者: 128,684 (+315) 公的機関のウェブサイトを確認する

感染状況 Infection status

- 🟢 [06/12] (EU) COVID-2020年6月11日現在の、世界で19件の状況アップデート 最近14日間の確定症例
- 🟢 [06/12] (EU) COVID-2020年6月11日現在の EU/EEAと英国の19つの状況アップデート 死亡数の合計
- 🟢 [06/12] (ドイツ) 連邦政府コロナウイルス(ドイツ)現在の症例数コロナウイルス 連邦政府コロナウイルス現在の症例数コロナウイルス
- 🟢 [06/11] (フランス) 日本の都市では、LCEを制限するために、LCEを歩きながらスマー… その結果、これらの歩行者の3分の2は、446人の衝突、103人の死者、21台の壊れた電話でシームレスに交差することができなかったことが明らかになった。
- 🟢 [06/11] (フランス) コロナウイルス: ドナルド・トランプ、フランスで最初の死者を報告

予防・緊急事態宣言 Prevention

- 🟢 [06/12] (EU) COVID-2020年6月11日現在の、世界で19件の状況アップデート ヨーロッパ疾病予防管理センター
- 🟢 [06/12] (EU) COVID-2020年6月11日現在の EU/EEAと英国の19つの状況アップデート ヨーロッパ疾病予防管理センター
- 🟢 [06/12] (ドイツ) RKI-アーカイブ2020-疫学情報24/2020 感染予防疫学情報
- 🟢 [06/12] (ドイツ) 連邦政府ホーム Warn App Actはパンデミックに関する情報を提供します 緊急事態情報およびメッセージアプリApp ACTは、すぐに重要な情報と現在のメッセージを提供しています。
- 🟢 [06/12] (ドイツ) 連邦政府ホーム Warn App Actはパンデミックに関する情報を提供します

症状・治療・検査など医療情報 Medical information

- 🟢 [06/12] (EU) COVID-2020年6月11日現在の、世界で19件の状況アップデート 症例の報告場所
- 🟢 [06/12] (EU) COVID-2020年6月11日現在の EU/EEAと英国の19つの状況アップデート EU/EEAおよび英国におけるCOVID-19の検査で確認された症例の分布
- 🟢 [06/12] (ドイツ) RKI-コロナウイルスSARS CoV2-10.6.2020の状況レポート SARS CoV2でPatientenを検査するためのHinweise
- 🟢 [06/12] (ドイツ) 連邦政府現在のシステム Ausbildungsberufe これらのフィールドにある多くの論文には、空席があります。
- 🟢 [06/12] (ドイツ) 連邦政府コロナウイルス(ドイツ)現在の症例数コロナウイルス

経済・福祉政策 Economics

- 🟢 [06/11] (ドイツ) 米連邦政府コロナウイルス病院および医療機関情報 コロナ・パンデミックの発症では、保護員が不足しているため、入手が困難であることが示されている。
- 🟢 [06/11] (ドイツ) ドイツ内での美術展および文化施設の支援 コロナ・パンデミックにより、保険会社および

休校・オンライン授業 Online lesson

- 🟢 [06/12] (ドイツ) 連邦政府現在のシステム Ausbildungsberufe 彼らは、業務や専門学校の組合せを利用して、成功を収めるために必要な作業を行うことができます。
- 🟢 [06/12] (ドイツ) 連邦政府ホーム 彼らは、業務や専門学校の組合せを利用して、成功を収めるために必要な作業を行うことができます。

その他 Others

- 🟢 [06/12] (ドイツ) RKI-アーカイブ2020-疫学情報24/2020
- 🟢 [06/12] (フランス) アリアナ・グランデって誰ですか? シー 米国の歌手は、市民を苦しめた攻撃によって、ヨーロッパのツアーを中止することに決めた。

Figure 3: The interface of the worldwide COVID-19 information aggregation system.

Website	Country	Primary	Reason	Topics
www.washingtonpost.com/coronavirus	US	True	I visit this URL daily and I trust them.	prevention and emergency declaration symptoms, medical treatment and tests economics and welfare
www.osha.gov/SLTC/covid-19	US	False	It helps employees and employers understand the work environment better as far as covid19 goes and how to stay healthy, safe and follow guidelines correctly.	prevention and emergency declaration symptoms, medical treatment and tests economics and welfare
www.mhlw.go.jp/stf/seisakunitsuite/bunya/0000164708_00001.html	Japan	True	The government provides reliable information.	infection status prevention and emergency declaration
vdata.nikkei.com/newsgraphics/coronavirus-world-map	Japan	False	I can learn the worldwide information through it.	infection status
www.ncbi.nlm.nih.gov/pubmed	Italy	True	A scientific papers site	symptoms, medical treatment and tests
www.ansa.it/canale_salutebenessere/	Italy	False	This is an official news outlet that gathers its news from trusted sources, it's a constantly updated website which a lot of Italians rely on. It also has exclusive reports and interviews to important people.	infection status prevention and emergency declaration symptoms, medical treatment and tests school and online classes about rumours
www.gouvernement.fr/info-coronavirus	France	True	This is French government website.	prevention and emergency declaration symptoms, medical treatment and tests
aatishb.com/covidtrends	France	False	The code is open source and the data come from reliable source	infection status
cnecovid.isciii.es	Spain	True	This site is the government web site	infection status prevention and emergency declaration symptoms, medical treatment and tests
www.marca.com/tiramillas/actualidad/2020/05/14/5ebcc0cee2704ec4bb8b4623.html	Spain	False	It is a sport magazine but they constantly update all the information in Spain about coronavirus	infection status entertainment and sports
www.charite.de	Germany	True	its the page of the hospital that mainly works with the german government	infection status
www.spiegel.de/thema/coronavirus/	Germany	False	one of Germanys oldest weekly news Paper, quality journalism and fact checking	infection status economics and welfare entertainment and sports
coronavirus.curitiba.pr.gov.br	Brazil	True	This is my city's COVID page, with daily updates on infection status and the running of the city, I can trust them because they only relay official information.	infection status prevention and emergency declaration
www.uol.com.br	Brazil	False	Its the biggest news site here in my country	prevention and emergency declaration entertainment and sports
www.mohfw.gov.in	India	True	This is the official page of the ministry of health and family welfare of government of India and is therefore reliable.	infection status prevention and emergency declaration symptoms, medical treatment and tests economics and welfare school and online classes entertainment and sports
www.thehindu.com	India	False	This is one of the trusted News paper	infection status prevention and emergency declaration economics and welfare school and online classes

Table 6: Some crowdsourcing results of reliable websites collection

Country	Website	Mentioned times
United States	www.cdc.gov/coronavirus/2019-ncov	14
	www.usa.gov/coronavirus	6
	www.nytimes.com/news-event/coronavirus	4
Japan	hazard.yahoo.co.jp/article/20200207	17
	www.mhlw.go.jp/...	13
	corona.feedal.com	6
Italy	www.salute.gov.it/nuovocoronavirus	11
	www.salute.gov.it/portale/home.html	4
	www.worldometers.info/coronavirus	3
France	www.gouvernement.fr/info-coronavirus	28
	www.who.int/fr/emergencies/diseases/novel-coronavirus-2019	7
	www.lemonde.fr/coronavirus-2019-ncov/	6
Spain	www.usa.gov/coronavirus	9
	www.mscbs.gob.es/profesionales/...	7
	covid19.gob.es	4
Germany	www.rki.de/DE/Home/homepage_node.html	7
	www.bundesgesundheitsministerium.de/coronavirus.html	6
	interaktiv.morgenpost.de/corona-virus-karte-infektionen-deutschland-weltweit	5
Brazil	covid.saude.gov.br	21
	g1.globo.com/bemestar/coronavirus	11
	coronavirus.saude.gov.br	9
India	www.worldometers.info/coronavirus	11
	www.mohfw.gov.in	10
	www.mygov.in/covid-19/?cbps=1	10

Table 7: Top three mentioned websites by crowdworkers of each country.