

CODA-19: Using a Non-Expert Crowd to Annotate Research Aspects on 10,000+ Abstracts in the COVID-19 Open Research Dataset

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Abstract

This paper introduces CODA-19¹, a human-annotated dataset that codes the **Background**, **Purpose**, **Method**, **Finding/Contribution**, and **Other** sections of 10,966 English abstracts in the COVID-19 Open Research Dataset. CODA-19 was created by 248 crowd workers from Amazon Mechanical Turk within 10 days, achieving a label quality comparable to that of experts. Each abstract was annotated by nine different workers, and the final labels were obtained by majority vote. The inter-annotator agreement (Cohen's kappa) between the crowd and the biomedical expert (0.741) is comparable to inter-expert agreement (0.788). CODA-19's labels have an accuracy of 82.2% when compared to the biomedical expert's labels, while the accuracy between experts was 85.0%. Reliable human annotations help scientists to understand the rapidly accelerating coronavirus literature and also serve as the battery of AI/NLP research, but obtaining expert annotations can be slow. We demonstrated that a non-expert crowd can be rapidly employed at scale to join the fight against COVID-19.

1 Introduction

Just as COVID-19 is spreading worldwide, the rapid acceleration in new coronavirus literature makes it hard to keep up with. Researchers have thus teamed up with the White House to release the COVID-19 Open Research Dataset (CORD-19) (Wang et al., 2020), containing 130,000+ related scholarly articles (as of August 13, 2020). The Open Research Dataset Challenge has also been launched on Kaggle to encourage researchers to use cutting-edge techniques to gain new insights from these papers (AI and collaborators, 2020). A

¹COVID-19 Research Aspect Dataset (CODA-19): <http://CODA-19.org>

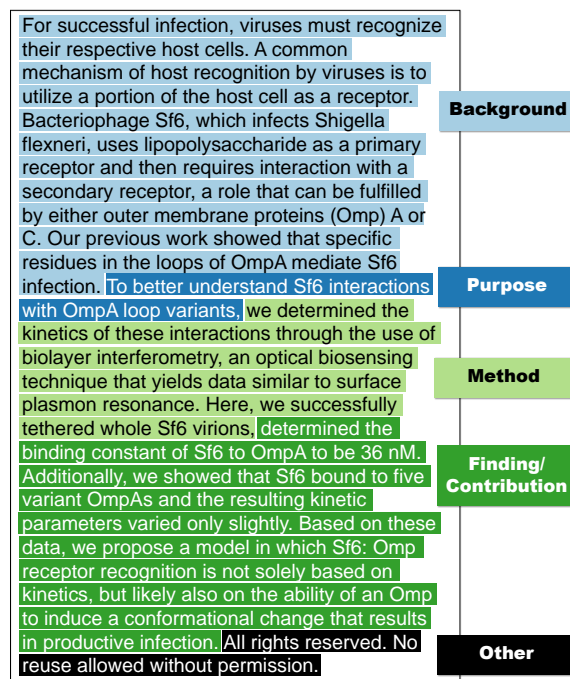


Figure 1: An example of the final crowd annotation for the abstract of (Hubbs et al., 2019).

key knowledge to comprehend scientific papers is that most papers follow a specific *structure* (Alley, 1996), where a set of components are presented in a particular order: a paper typically begins with the background information, such as the motivation and the known facts relevant to the problem, followed by the methods that the authors used to study the problem, and eventually presents the results and discusses the implications (Dasigi et al., 2017). Knowing this structure is essential to comprehend the core arguments and contributions of a paper effectively. Prior work, as shown in Table 1, has proposed various schemes to analyze the structures of scientific articles. Parsing all the CORD-19's papers automatically and represent their structures using a semantic scheme (e.g., background,

	Corpus	Document type	Instance type	# of documents	# of sentence	Annotator type	# of classes	Public?
This work	CORD-19	abstract	clause	10,966	103,978	crowd	5	yes
Liakata et al.	ART†	paper	sentence	225	35,040	expert	18	yes
Ravenscroft et al.	MCCRA†	paper	sentence	50	8,501	expert	18	yes
Teufel and Moens	CONF	paper	sentence	80	12,188	expert	7	no
Kim et al.	MEDLINE	abstract	sentence	1,000	10,379	expert	6	no
Contractor et al.	PubMed	paper	sentence	50	8,569	expert	8	no
Morid et al.	UpToDate+PubMed	mixed	sentence	158	5,896	expert	8	no
Banerjee et al.	CONF+arXiv	paper	sentence	450	4,165	expert	3	no
Huang and Chen	NTHU database	abstract	sentence	597	3,394	expert	5	no
Agarwal and Yu	BioMed Central	paper	sentence	148	2,960	expert	5	no
Hara and Matsumoto	MEDLINE	abstract	sentence	200	2,390	expert	5	no
Zhao et al.	JOUR	mixed	sentence	...	2,000	expert	5	no
McKnight and Srinivasan	MEDLINE	abstract	sentence	204	1,532	...	4	no
Chung	PubMed	abstract	sentence	318	829	expert	4	no
Wu et al.	CiteSeer	abstract	sentence	106	709	expert	5	no
Dasigi et al.	PubMed	section	clause	75	<4,497*	expert	7	no
Ruch et al.	PubMed	abstract	sentence	100	4	no
Lin et al.	PubMed	abstract	sentence	49	...	expert	4	no

Table 1: Comparison of datasets, excluding structured abstracts. Abbreviations CONF and JOUR mean conference and journal papers, respectively. The dagger symbol † means that the corpus is self-curated. The “mixed” document type means that the dataset contains instances from both full papers and abstracts. Symbol “...” means unknown. The last “Public” column means if the dataset is publicly downloadable on the Internet. The symbol * means that the work only provides the number of clauses (sentence fragments).

method, result, etc.) will make it easier for both humans and machines to comprehend and process the information in these 13,000+ papers.

Modern automated language understanding approaches often require large-scale human annotations as training data to reach good performance levels. Researchers traditionally relied on experts to annotate the structures of scientific papers, as shown in Table 1. However, producing such annotations for thousands of papers will be a prolonged process if we only employ experts, whose availability is much more limited than that of non-expert annotators. As a consequence, most of the human-annotated corpora that labeled the structures of scientific articles covered no more than one thousand papers (Table 1). Obtaining expert annotations can be too slow to respond to COVID-19, so we explore an alternative approach: using **non-expert crowds**, such as workers on Amazon Mechanical Turk (MTurk), to produce high-quality, useful annotations for thousands of scientific papers.

Researchers have used non-expert crowds to annotate text, for example, for machine translation (Wijaya et al., 2017; Gao et al., 2015; Yan et al., 2014; Zaidan and Callison-Burch, 2011; Post et al., 2012), natural language inference (Bowman et al., 2015; Khot et al., 2018), or medical report analysis (Maclean and Heer, 2013; Zhai et al., 2013; Good et al., 2014; Li et al., 2016). While domain

experts are still valuable in creating high-quality labels (Stubbs, 2013; Pustejovsky and Stubbs, 2012), and concerns have also been raised over the uses of MTurk (Fort et al., 2011; Cohen et al., 2016), employing non-expert crowds has been shown to be an effective and scalable approach to create datasets. However, annotating *papers* is still often viewed as an “expert task”. Majority of the datasets only used experts (Table 1) or the information provided by the paper authors (Table 2) to denote the structures of scientific papers. One exception was the SOLVENT project by Chan *et al.* (2018). They recruited MTurk workers to annotate tokens in paper abstracts with the research aspects (*e.g.*, Background, Mechanism, Finding). However, while the professional editors recruited from Upwork performed well, the MTurk workers’ token-level accuracy was only 59%, which was insufficient for training good machine-learning models.

This paper introduces **CODA-19**, the **COVID-19 Research Aspect Dataset**, presenting the first outcome of our exploration in using non-expert crowds for large-scale scholarly article annotation. CODA-19 contains 10,966 abstracts randomly selected from CORD-19. Each abstract was segmented into sentences, which were further divided into one or more shorter text fragments. All 168,286 text fragments in CODA-19 were labeled with a “research aspect,” *i.e.*, **Background, Pur-**

	Corpus	Document	Instance	# of documents	# of sentence	# of classes	Public?
Dernoncourt and Lee	PubMed	structured abstract	sentence	195K	2.2M	5	yes
Jin and Szolovits	PubMed	structured abstract	sentence	24K	319K	7	yes
Huang et al.	MEDLINE	structured abstract	sentence	19K	526K	3	no
Boudin et al.	PubMed	structured abstract	sentence	260K	349K	3	no
Banerjee et al.	PubMed	structured abstract	sentence	20K	216K	3	no
Chung	PubMed	structured abstract	sentence	13K	156K	4	no
Shimbo et al.	MEDLINE	structured abstract	sentence	11K	114K	5	no
McKnight and Srinivasan	MEDLINE	structured abstract	sentence	7K	90K	4	no
Chung and Coiera	MEDLINE	structured abstract	sentence	3K	45K	5	no
Hirohata et al.	MEDLINE	structured abstract	sentence	683K	...	4	no
Lin et al.	MEDLINE	structured abstract	sentence	308K	...	4	no
Ruch et al.	PubMed	structured abstract	sentence	12K	...	4	no

Table 2: Comparison of datasets, leveraging structured abstracts that do not require human-labeling effort. Some works that involve human-labeled data are also present in Table 1.

pose, Method, Finding/Contribution, or Other.

This annotation scheme was adapted from SOLVENT (Chan et al., 2018), with minor changes. Figure 1 shows an example annotated abstract.

In our project, 248 crowd workers from MTurk were recruited and annotated the whole CODA-19 **within ten days**.² Each abstract was annotated by nine different workers. We aggregated the crowd labels for each text segment using majority voting.

The resulting crowd labels had a label accuracy of 82% when compared against the expert labels on 129 abstracts. The inter-annotator agreement (Cohen’s kappa) was 0.741 between the crowd labels and the expert labels, while it was 0.788 between two experts. We also established several classification baselines, showing the feasibility of automating such annotation tasks.

2 Related Work

A significant body of prior work have explored the space of revealing or parsing the structures of scientific articles, including composing structured abstracts (Hartley, 2004), identifying argumentative zones (Teufel et al., 1999; Mizuta et al., 2006; Liakata et al., 2010), analyzing scientific discourse (de Waard and Maat, 2012; Dasigi et al., 2017; Banerjee et al., 2020), supporting paper writing (Wang et al., 2019; Huang and Chen, 2017), and representing papers to reduce information overload (de Waard et al., 2009). In this section, we review the datasets that were created to study the structures of scientific articles.

We categorize all the datasets that denoted the structures of scientific papers into two categories:

²From April 19, 2020 to April 29, 2020, including the time for worker training and post-task survey.

(i) the datasets that used human labors to manually annotate the sentences in scientific articles (Table 1), and (ii) the datasets that leveraged the structured abstracts (Table 2).

In the first category, the researchers recruited a group of annotators— often experts, such as medical doctors, biologists, or computer scientists— to manually label the sentences in papers with their research aspects (*e.g.*, background, method, finding). CODA-19 belongs to the first category. Table 1 reviews the existing datasets in this category. To the best of our knowledge, only two other datasets can be download from the Internet besides our work. Nearly all of the datasets of this kind were annotated by domain experts or researchers, which thus limited their sizes significantly. In Table 1, CODA-19 is the only dataset that contains more than one thousand papers. Our work presents a scalable and efficient solution that employs non-expert crowd workers to annotate scientific papers. Furthermore, our labels were based on clauses (also referred to as sentence fragments or sub-sentences), which provide more detailed information than the majority of other works that used sentence-level annotations.

In the second category, researchers used the section titles that came with structured abstracts in scientific databases (*e.g.*, PubMed) to label sentences. A structured abstract is an abstract with distinct, labeled sections (*e.g.*, Introduction, Methods, Results) (Hartley, 2004). Different journals have different guidelines for section titles. To form a coherent and standardized dataset, researchers often mapped these different titles into a smaller set of labels. The sizes of the datasets in the second category (Table 2) were typically larger because they did not require extra annotating effort. This

line of research is inspiring, however, assigning the same label to all the sentences in the same section overlooks the information granularity at the sentence level. Furthermore, not every journal uses the format of structured abstracts. The language used for describing a research work with a coherent paragraph might defer from the language used for presenting the work with a set of predetermined sections. Our work creates an in-domain dataset with high-quality labels for each sentence fragment in the 10,000+ abstracts, regardless of their formats.

3 CODA-19 Dataset Construction

CODA-19 has 10,966 abstracts that contain a total of 2,703,174 tokens and 103,978 sentences, which were divided into 168,286 segments. The data is released as a 80/10/10 train/dev/test split.

3.1 Annotation Scheme

CODA-19 uses a five-class annotation scheme to denote research aspects in scientific articles: **Background, Purpose, Method, Finding/Contribution, or Other**. Table 3 shows the full annotation guidelines we developed to instruct workers. We updated and expanded this guideline daily during the annotation process to address workers' questions and feedback. This scheme was adapted from SOLVENT (Chan et al., 2018), with three changes. First, we added an "Other" category. Articles in CODA-19 are broad and diverse (Colavizza et al., 2020), so it is unrealistic to govern all cases with only four categories. We are also aware that CODA-19's data came with occasional formatting or segmenting errors. These cases were also to be put into the "Other" category. Second, we replaced the "Mechanism" category with "Method." Chan et al. created SOLVENT with the aim of discovering the analogies between research papers at scale. Our goal was to better understand the contribution of each paper, so we decided to use a more general word, "Method," to include the research methods and procedures that cannot be characterized as "Mechanisms." Also, biomedical literature widely used the word "mechanism," which could also be confusing to workers. Third, we modified the name "Finding" to "Finding/Contribution" to allow broader contributions that are not usually viewed as "findings."

3.2 Data Preparation

We used Stanford CoreNLP (Manning et al., 2014) to tokenize and segment sentences for all the abstracts in CODA-19. We further used comma (,), semicolon (;), and period (.) to split each sentence into shorter fragments, where a fragment has no fewer than six tokens (including punctuation marks) and has no orphan parentheses.

As of April 15, 2020, 29,306 articles in CODA-19 had a non-empty abstract. An average abstract had 9.73 sentences (SD = 8.44), which were further divided into 15.75 text segments (SD = 13.26). Each abstract had 252.36 tokens (SD = 192.89) on average. We filtered out the 538 (1.84%) abstracts with only one sentence because many of them had formatting errors. We also removed the 145 (0.49%) abstracts that had more than 1,200 tokens to keep the working time for each task under five minutes (see Section 3.4). We randomly selected 11,000 abstracts from the remaining data for annotation. During the annotation process, workers informed us that a few articles were not in English. We identified these automatically using `langdetect`³ and excluded them.

3.3 Interface Design

Figure 2 shows the worker interface, which we designed to guide workers to read and label all the text segments in an abstract. The interface showed the instruction on the top (Figure 2a) and presented the task in three steps: In Step 1, the worker was instructed to spend ten seconds to take a quick glance at the abstract. The goal was to get a high-level sense of the topic rather than to fully understand the abstract. In Step 2, we showed the main annotation interface (Figure 2b), where the worker can go through each text segment and select the most appropriate category for each segment one by one. In Step 3, the worker can review the labeled text segments (Figure 2c) and go back to Step 2 to fix any problems.

3.4 Annotation Procedure

Worker Training and Recruitment We first created a qualification Human Intelligence Task (HIT) to recruit workers on MTurk (\$1/HIT). The workers needed to watch a five-minute video to learn the scheme, go through an interactive tutorial to learn the interface, and sign a consent form to

³langdetect: <https://github.com/Mimino666/langdetect>

Aspect	Annotation Guideline
Background	<p>“Background” text segments answer one or more of these questions:</p> <ul style="list-style-type: none"> • Why is this problem important? • What relevant works have been created before? • What is still missing in the previous works? • What are the high-level research questions? • How might this help other research or researchers?
Purpose	<p>“Purpose” text segments answer one or more of these questions:</p> <ul style="list-style-type: none"> • What specific things do the researchers want to do? • What specific knowledge do the researchers want to gain? • What specific hypothesis do the researchers want to test?
Method	<p>“Method” text segments answer one or more of these questions:</p> <ul style="list-style-type: none"> • How did the researchers do the work or find what they sought? • What are the procedures and steps of the research?
Finding/Contribution	<p>“Finding/Contribution” text segments answer one or more of these questions:</p> <ul style="list-style-type: none"> • What did the researchers find out? • Did the proposed methods work? • Did the thing behave as the researchers expected?
Other	<ul style="list-style-type: none"> • Text segments that do <i>not</i> fit into any of the four categories above. • Text segments that are <i>not</i> part of the article. • Text segments that are <i>not</i> in English. • Text segments that contain <i>only</i> reference marks (e.g., “[1,2,3,4,5]”) or dates (e.g., “April 20, 2008”). • Captions for figures and tables (e.g. “Figure 1: Experimental Result of ...”) • Formatting errors. • Text segments the annotator does not know or is not sure about.

Table 3: CODA-19’s annotation guideline for crowd workers.

obtain the qualification. We granted custom qualifications to 400 workers who accomplished the qualification HIT. Only the workers with this qualification could do our tasks.⁴

Posting Tasks in Smaller Batches We divided 11,000 abstracts into smaller batches, where each batch has no more than 1,000 abstracts. Each abstract forms a single HIT. We recruited nine different workers through nine assignments to label each abstract. Our strategy was to post one batch at a time. When a batch was finished, we assessed its data quality, sent feedback to workers to guide them, or blocked workers who constantly had low accuracy before proceeding with the next batch.

Worker Wage and Total Cost We aimed to pay an hourly wage of \$10. The working time of an abstract was estimated by the average reading speed of English native speakers, *i.e.*, 200-300 words per minute (Siegenthaler et al., 2012). For an abstract, we rounded up ($\#token/250$) to an integer as the estimated working time in minutes and paid ($\$0.05 + \text{Estimated Working Minutes} \times \0.17) for it. As a result, 59.49% of our HITs were priced at \$0.22, 36.41% were at \$0.39, 2.74% were at \$0.56,

0.81% were at \$0.73, and 0.55% were at \$0.90. We posted nine assignments per HIT. Adding the 20% MTurk fee, coding each abstract (using nine workers) cost \$3.21 on average.

In this project, each worker received an average of $(\$3.21/9)/1.2 = \0.297 for annotating one abstract. We empirically learned that the CS Expert (see Section 4) spent an average of 50.8 seconds (SD=10.4, N=10) to annotate an abstract, yielding an estimated hourly wage of $\$0.297 \times (60 \times 60/50.8) = \21.05 ; and the MTurk workers in SOLVENT took a median of 1.3 minutes to annotate one abstract (Chan et al., 2018), yielding an estimated hourly wage of $\$0.297 \times (60/1.3) = \13.71 . We thus believe that the actual hour wage for workers were close to or over \$10.

3.5 Label Aggregation

The final labels in CODA-19 were obtained by majority voting over crowd labels, excluding the labels from blocked workers. For each batch of HITs, we manually examined the labels from workers who frequently disagreed with the majority-voted labels (Section 3.4). If a worker had abnormally low accuracy or was apparently spamming, we retracted the worker’s qualification to prevent him/her from taking future tasks. We excluded the labels from these removed workers when aggregating the final

⁴Four built-in MTurk qualifications were also used: Locale (US Only), HIT Approval Rate ($\geq 98\%$), Number of Approved HITs (≥ 3000), and the Adult Content Qualification.

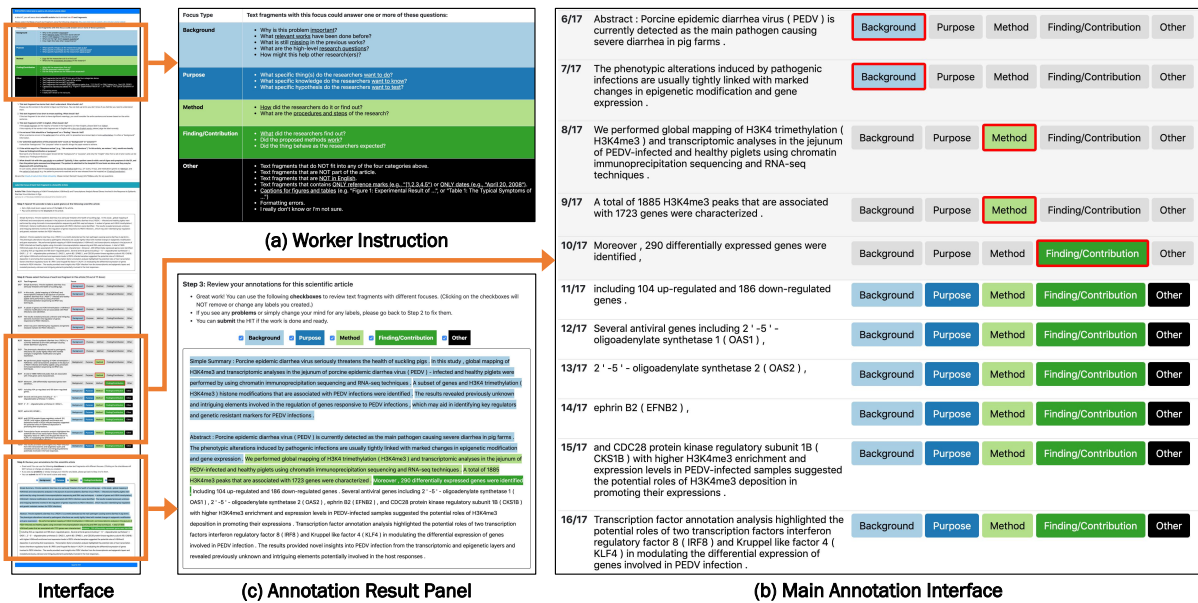


Figure 2: The worker interface of CODA-19.

labels. Note that there can be ties when two or more aspects received the same highest number of votes (e.g., 4/4/1 or 3/3/3). We resolved ties by using the following tiebreakers, in order: Finding, Method, Purpose, Background, Other.

4 Data Quality Assessment

We worked with a biomedical expert and a computer scientist to assess label quality; both experts are co-authors of this paper. The biomedical expert (the “Bio” Expert in Table 4) is an MD and also a PhD in Genetics and Genomics. She is now a resident physician in pathology at the University of California, San Francisco. The other expert (the “CS” Expert in Table 4) has a PhD in Computer Science and is currently a Project Scientist at Carnegie Mellon University.

Both experts annotated the same 129 abstracts randomly selected from CODA-19. The experts used the same interface as that of the workers (Figure 2). We used scikit-learn’s implementation (Pedregosa et al., 2011) to compute the inter-annotator agreement (Cohen’s kappa). The kappa between the two experts was 0.788. Table 4 shows the aggregated crowd label’s accuracy, along with the precision, recall, and F1-score of each class. CODA-19’s labels have an accuracy of 0.82 and a kappa of 0.74 when compared against the two experts’ labels. It is noteworthy that when we compared labels between the two experts, the accuracy (0.850) and kappa (0.788) were only slightly higher. The

crowd workers performed best in labeling “Background” and “Finding,” and they had nearly perfect precision for the “Other” category. Figure 3 shows the normalized confusion matrix for the aggregated crowd labels versus the biomedical expert’s labels. Many “Purpose” segments were mislabeled as “Background,” which might indicate more ambiguous cases between these two categories. During the annotation period, we received several emails from workers asking about the distinctions between these two aspects. For example, does “potential applications of the proposed work” count as “Background” or “Purpose”?

5 Classification Baselines

We further examined machines’ capacity for annotating research aspects automatically. Seven baseline models were implemented: Linear SVM, Random Forest, Multinomial Naive Bayes (MNB), CNN, LSTM, BERT, and SciBERT.

Data Preprocessing The tf-idf feature was used for Linear SVM and Random Forest. We turned all words into lowercase and removed those with frequency lower than 5. The final tf-idf feature contained 16,775 dimensions. Two variations of feature were used for MNB, the n-gram counts feature and the n-gram tf-idf feature. Using grid search method, the n-gram counts feature combining unigram, bigram, and trigram with minimum frequency of 3 yielded the best result. The final n-gram feature contained 181,391 dimensions. The

Eval. Label	Gold Label	Background			Purpose			Method			Finding			Other			acc	kappa
		P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1		
Crowd	Bio	.827	.911	.867	.427	.662	.519	.783	.710	.744	.874	.838	.856	.986	.609	.753	.822	.741
Crowd	CS	.846	.883	.864	.700	.611	.653	.818	.633	.714	.800	.931	.860	.986	.619	.761	.821	.745
CS	Bio	.915	.966	.940	.421	.746	.538	.670	.785	.723	.958	.789	.865	.867	.852	.860	.850	.788

Table 4: Crowd performance using both Bio Expert and CS Expert as the gold standard. CODA-19’s labels have an accuracy of 0.82 and a kappa of 0.74, when compared against two experts’ labels. It is noteworthy that when we compared labels between two experts, the accuracy (0.850) and kappa (0.788) were only slightly higher.

Model	Background			Purpose			Method			Finding			Other			Accuracy
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	
# Sample	5062			821			2140			6890			562			15475
SVM	.658	.703	.680	.621	.446	.519	.615	.495	.549	.697	.729	.712	.729	.699	.714	.672
RF	.671	.632	.651	.696	.365	.479	.716	.350	.471	.630	.787	.699	.674	.742	.706	.652
MNB-count	.654	.714	.683	.549	.514	.531	.570	.585	.577	.711	.691	.701	.824	.425	.561	.665
MNB-tfidf	.655	.683	.669	.673	.391	.495	.640	.469	.541	.661	.754	.704	.757	.383	.508	.659
CNN	.649	.706	.676	.612	.512	.557	.596	.562	.579	.726	.702	.714	.743	.795	.768	.677
LSTM	.655	.706	.680	.700	.464	.558	.634	.508	.564	.700	.724	.711	.682	.770	.723	.676
BERT	.719	.759	.738	.585	.639	.611	.680	.612	.644	.777	.752	.764	.773	.874	.820	.733
SciBERT	.733	.768	.750	.616	.636	.626	.715	.636	.673	.783	.775	.779	.794	.852	.822	.749

Table 5: Baseline performance of automatic labeling using the crowd labels of CODA-19. SciBERT achieves highest accuracy of 0.749 and outperforms other models in every aspects.

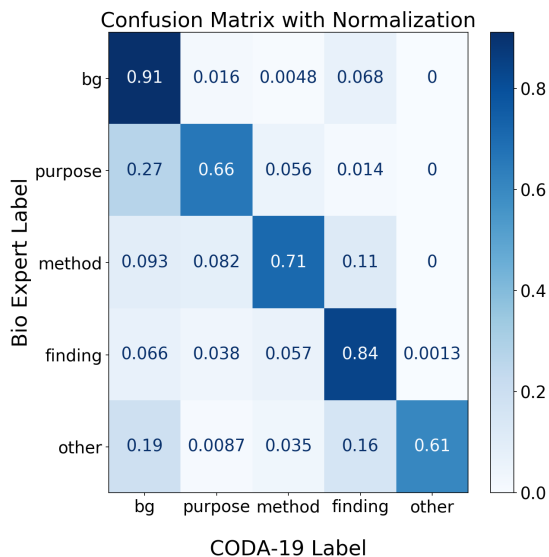


Figure 3: The normalized confusion matrix for the CODA-19 labels versus the biomedical expert’s labels.

n-gram tf-idf feature combining unigram, bigram, and trigram with minimum frequency of 10 yielded the best result where the dimensions is 41,966. For deep-learning approaches, the vocabulary size was 16,135, where tokens with frequency lower than 5 were replaced by <UNK>. Sequences were padded with <PAD> if containing less than 60 tokens and were truncated if containing more than 60 tokens.

Models Machine-learning approaches were implemented using Scikit-learn (Pedregosa et al., 2011) and deep-learning approaches were implemented using PyTorch (Paszke et al., 2019). The following are the training setups.

- **Linear SVM:** We did a grid search for hyper-parameters and found that $C = 1$, $tol = 0.001$, and *hinge loss* yielded the best results.
- **Random Forest:** With the grid search, 150 estimators yielded the best result.
- **Multinomial Naive Bayes (MNB):** Several important early works used Naive Bayes models for text classification (Rennie et al., 2003; McCallum et al., 1998). When using n-gram counts as the feature, the default parameter, $alpha = 1.0$, yielded the best result. For the one using n-gram tf-idf feature, $alpha = 0.5$ yielded the best result.
- **CNN:** The classic CNN (Kim, 2014) was implemented. Three kernel sizes (3, 4, 5) were used, each with 100 filters. The word embedding size was 256. A dropout rate of 0.3 and L2 regularization with weight $1e - 6$ were used when training. We used the Adam optimizer, with a learning rate of $5e - 5$. The model was trained for 50 epochs and the one

with highest validation score was kept for testing.

- **LSTM:** We used 10 LSTM layers to encode the sequence. The encoded vector was then passed through a dense layer for classification. The word embedding size and the LSTM hidden size were both 256. The rest of the hyperparameter and training setting was the same as that of the CNN model.
- **BERT:** Hugging Face’s implementation (Wolf et al., 2019) of the Pretrained BERT (Devlin et al., 2018) was used for fine-tuning. We fine-tuned the pretrained model with a learning rate of $3e - 7$ for 50 epochs. Early stopping was used when no improvement occurred in the validation accuracy for five consecutive epochs. The model with the highest validation score was kept for testing.
- **SciBERT:** Hugging Face’s implementation (Wolf et al., 2019) of the Pretrained SciBERT (Beltagy et al., 2019) was used for fine-tuning. The fine-tuning setting is the same as that of the BERT model.

Result Table 5 shows the results for the six baseline models: SciBERT preformed the best in overall accuracy. When looking at each aspect, all the models performed better in classifying “Background,” “Finding,” and “Other,” while identifying “Purpose” and “Method” was more challenging.

6 Discussion

Annotating scientific papers was often viewed as an “expert task” that is difficult or impossible for non-expert annotators to do. Many datasets that labeled scientific papers were thus produced by small groups of experts. For example, two researchers manually created the ACL RD-TEC 2.0, a dataset that contains 300 scientific abstracts (QasemiZadeh and Schumann, 2016); a group of annotators “with rich experience in biomedical content curation” created MedMentions, a corpus containing 4,000 abstracts (Mohan and Li, 2019); and many datasets used in biomedical NLP shared tasks were manually created by the organizers and/or their students, such as the ScienceIE in SemEval’17 (Augenstein et al., 2017) and Relation Extraction in SemEval’18 (Gábor et al., 2018). Our work sug-

gests that non-expert crowds can be used for these types of data-labeling tasks.

Prior work often used crowd workers to annotate pieces of lower-level information on papers or medical documents, such as images (Heim et al., 2018) or named entities (*e.g.*, medical terms (Mohan and Li, 2019), disease (Good et al., 2014), medicine (Abaho et al., 2019).) Our work shows that crowd workers, to certain extent, can comprehend the high-level structures and discourses in papers, and therefore could be assigned with more complex, higher-level tasks.

7 Conclusion and Future Work

This paper introduces CODA-19, a human-annotated dataset that codes the Background, Purpose, Method, Finding/Contribution, and Other sections of 10,966 English abstracts in the COVID-19 Open Research Dataset. CODA-19 was created by a group of MTurk workers, achieving a label quality comparable to that of experts. We demonstrated that a non-expert crowd can be rapidly employed at scale to join the fight against COVID-19.

One future direction is to improve classification performance. We evaluated the automatic labels against the biomedical expert’s labels, and the SciBERT model achieved an accuracy of 0.774 and a Cohen’s kappa of 0.667, indicating some space for further improvement. Furthermore, one motivation for spotting research aspects automatically is to help search and information extraction (Teufel et al., 1999). We have teamed up with the group who created COVIDSeer⁵ to explore the possible uses of CODA-19 in such systems.

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⁵CovidSeer: <https://covidseer.ist.psu.edu/>

References

- Micheal Abaho, Danushka Bollegala, Paula Williamson, and Susanna Dodd. 2019. Correcting crowdsourced annotations to improve detection of outcome types in evidence based medicine. In *CEUR Workshop Proceedings*, volume 2429, pages 1–5.
- Shashank Agarwal and Hong Yu. 2009. Automatically classifying sentences in full-text biomedical articles into introduction, methods, results and discussion. *Bioinformatics*, 25(23):3174–3180.
- Allen Institute For AI and 8 collaborators. 2020. [Covid-19 open research dataset challenge \(cord-19\)](#) — kaggle.
- Michael Alley. 1996. The craft of scientific writing. Technical report, Springer.
- Isabelle Augenstein, Mrinal Das, Sebastian Riedel, Lakshmi Vikraman, and Andrew McCallum. 2017. Semeval 2017 task 10: Scienceie-extracting keyphrases and relations from scientific publications. *arXiv preprint arXiv:1704.02853*.
- Soumya Banerjee, Debarshi Kumar Sanyal, Samiran Chattopadhyay, Plaban Kumar Bhowmick, and Parthapratim Das. 2020. Segmenting scientific abstracts into discourse categories: A deep learning-based approach for sparse labeled data. *arXiv preprint arXiv:2005.05414*.
- Iz Beltagy, Kyle Lo, and Arman Cohan. 2019. Scibert: A pretrained language model for scientific text. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3606–3611.
- Florian Boudin, Jian-Yun Nie, Joan C Bartlett, Roland Grad, Pierre Pluye, and Martin Dawes. 2010. Combining classifiers for robust pico element detection. *BMC medical informatics and decision making*, 10(1):29.
- Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. [A large annotated corpus for learning natural language inference](#). In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 632–642, Lisbon, Portugal. Association for Computational Linguistics.
- Joel Chan, Joseph Chee Chang, Tom Hope, Dafna Shahaf, and Aniket Kittur. 2018. Solvent: A mixed initiative system for finding analogies between research papers. *Proceedings of the ACM on Human-Computer Interaction*, 2(CSCW):1–21.
- Grace Chung and Enrico Coiera. 2007. A study of structured clinical abstracts and the semantic classification of sentences. In *Biological, translational, and clinical language processing*, pages 121–128.
- Grace Y Chung. 2009. Sentence retrieval for abstracts of randomized controlled trials. *BMC medical informatics and decision making*, 9(1):10.
- K Bretonnel Cohen, Karën Fort, Gilles Adda, Sophia Zhou, and Dimeji Farri. 2016. Ethical issues in corpus linguistics and annotation: Pay per hit does not affect effective hourly rate for linguistic resource development on amazon mechanical turk. In *LREC... International Conference on Language Resources & Evaluation:[proceedings]. International Conference on Language Resources and Evaluation*, volume 2016, page 8. NIH Public Access.
- Giovanni Colavizza, Rodrigo Costas, Vincent A. Traag, Nees Jan van Eck, Thed van Leeuwen, and Ludo Waltman. 2020. [A scientometric overview of cord-19](#). *bioRxiv*.
- Danish Contractor, Yufan Guo, and Anna Korhonen. 2012. Using argumentative zones for extractive summarization of scientific articles. In *Proceedings of COLING 2012*, pages 663–678.
- Pradeep Dasigi, Gully APC Burns, Eduard Hovy, and Anita de Waard. 2017. Experiment segmentation in scientific discourse as clause-level structured prediction using recurrent neural networks. *arXiv preprint arXiv:1702.05398*.
- Franck Dernoncourt and Ji Young Lee. 2017. Pubmed 200k rct: a dataset for sequential sentence classification in medical abstracts. *arXiv preprint arXiv:1710.06071*.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.
- Karën Fort, Gilles Adda, and K Bretonnel Cohen. 2011. Amazon mechanical turk: Gold mine or coal mine? *Computational Linguistics*, 37(2):413–420.
- Kata Gábor, Davide Buscaldi, Anne-Kathrin Schumann, Behrang QasemiZadeh, Haifa Zargayouna, and Thierry Charnois. 2018. Semeval-2018 task 7: Semantic relation extraction and classification in scientific papers. In *Proceedings of The 12th International Workshop on Semantic Evaluation*, pages 679–688.
- Mingkun Gao, Wei Xu, and Chris Callison-Burch. 2015. [Cost optimization in crowdsourcing translation](#). In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics (NAACL 2015)*, Denver, Colorado.
- Benjamin M Good, Max Nanis, Chunlei Wu, and Andrew I Su. 2014. Microtask crowdsourcing for disease mention annotation in pubmed abstracts. In *Pacific Symposium on Biocomputing Co-Chairs*, pages 282–293. World Scientific.

- Kazuo Hara and Yuji Matsumoto. 2007. Extracting clinical trial design information from medline abstracts. *New Generation Computing*, 25(3):263–275.
- James Hartley. 2004. Current findings from research on structured abstracts. *Journal of the Medical Library Association*, 92(3):368.
- Eric Heim, Tobias Roß, Alexander Seitel, Keno März, Bram Stieltjes, Matthias Eisenmann, Johannes Lebert, Jasmin Metzger, Gregor Sommer, Alexander W Sauter, et al. 2018. Large-scale medical image annotation with crowd-powered algorithms. *Journal of Medical Imaging*, 5(3):034002.
- Kenji Hirohata, Naoaki Okazaki, Sophia Ananiadou, and Mitsuru Ishizuka. 2008. Identifying sections in scientific abstracts using conditional random fields. In *Proceedings of the Third International Joint Conference on Natural Language Processing: Volume-I*.
- Hen-Hsen Huang and Hsin-Hsi Chen. 2017. Disa: A scientific writing advisor with deep information structure analysis. In *IJCAI*, pages 5229–5231.
- Ke-Chun Huang, I-Jen Chiang, Furen Xiao, Chun-Chih Liao, Charles Chih-Ho Liu, and Jau-Min Wong. 2013. Pico element detection in medical text without metadata: Are first sentences enough? *Journal of biomedical informatics*, 46(5):940–946.
- Natalia B Hubbs, Mareena M Whisby-Pitts, and Jonathan L McMurry. 2019. Kinetic analysis of bacteriophage sf6 binding to outer membrane protein a using whole virions. *bioRxiv*, page 509141.
- Di Jin and Peter Szolovits. 2018. Pico element detection in medical text via long short-term memory neural networks. In *Proceedings of the BioNLP 2018 workshop*, pages 67–75.
- Tushar Khot, Ashish Sabharwal, and Peter Clark. 2018. [Scitail: A textual entailment dataset from science question answering](#).
- Su Nam Kim, David Martinez, Lawrence Cavedon, and Lars Yencken. 2011. Automatic classification of sentences to support evidence based medicine. In *BMC bioinformatics*, volume 12, page S5. Springer.
- Yoon Kim. 2014. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882*.
- Tong Li, Àlex Bravo, Laura I Furlong, Benjamin Good, and Andrew Su. 2016. [A crowdsourcing workflow for extracting chemical-induced disease relations from free text](#). *Database*, 2016:baw051.
- Maria Liakata, Larisa N Soldatova, et al. 2009. Semantic annotation of papers: Interface & enrichment tool (sapient). In *Proceedings of the Workshop on Current Trends in Biomedical Natural Language Processing*, pages 193–200. Association for Computational Linguistics.
- Maria Liakata, Simone Teufel, Advait Siddharthan, and Colin Batchelor. 2010. Corpora for the conceptualisation and zoning of scientific papers. In *Proceedings of the Seventh conference on International Language Resources and Evaluation (LREC'10)*.
- Jimmy Lin, Damianos Karakos, Dina Demner-Fushman, and Sanjeev Khudanpur. 2006. Generative content models for structural analysis of medical abstracts. In *Proceedings of the hlt-naacl bionlp workshop on linking natural language and biology*, pages 65–72.
- Diana Maclean and Jeffrey Heer. 2013. [Identifying medical terms in patient-authored text: A crowdsourcing-based approach](#). *Journal of the American Medical Informatics Association : JAMIA*, 20.
- Christopher D. Manning, Mihai Surdeanu, John Bauer, Jenny Finkel, Steven J. Bethard, and David McClosky. 2014. [The Stanford CoreNLP natural language processing toolkit](#). In *Association for Computational Linguistics (ACL) System Demonstrations*, pages 55–60.
- Andrew McCallum, Kamal Nigam, et al. 1998. A comparison of event models for naive bayes text classification. In *AAAI-98 workshop on learning for text categorization*, volume 752, pages 41–48. Citeseer.
- Larry McKnight and Padmini Srinivasan. 2003. Categorization of sentence types in medical abstracts. In *AMIA Annual Symposium Proceedings*, volume 2003, page 440. American Medical Informatics Association.
- Yoko Mizuta, Anna Korhonen, Tony Mullen, and Nigel Collier. 2006. Zone analysis in biology articles as a basis for information extraction. *International journal of medical informatics*, 75(6):468–487.
- Sunil Mohan and Donghui Li. 2019. Medmentions: a large biomedical corpus annotated with umls concepts. *arXiv preprint arXiv:1902.09476*.
- Mohammad Amin Morid, Marcelo Fiszman, Kalpana Raja, Siddhartha R Jonnalagadda, and Guilherme Del Fiol. 2016. Classification of clinically useful sentences in clinical evidence resources. *Journal of biomedical informatics*, 60:14–22.
- Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. [Pytorch: An imperative style, high-performance deep learning library](#). In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc.

- Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, Jake Vanderplas, Alexandre Passos, David Cournapeau, Matthieu Brucher, Matthieu Perrot, and Édouard Duchesnay. 2011. Scikit-learn: Machine learning in python. *J. Mach. Learn. Res.*, 12(null):2825–2830.
- Matt Post, Chris Callison-Burch, and Miles Osborne. 2012. [Constructing parallel corpora for six Indian languages via crowdsourcing](#). In *Proceedings of the Seventh Workshop on Statistical Machine Translation*, pages 401–409, Montréal, Canada. Association for Computational Linguistics.
- James Pustejovsky and Amber Stubbs. 2012. *Natural Language Annotation for Machine Learning: A guide to corpus-building for applications*. ” O’Reilly Media, Inc.”.
- Behrang QasemiZadeh and Anne-Kathrin Schumann. 2016. The acl rd-tec 2.0: A language resource for evaluating term extraction and entity recognition methods. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16)*, pages 1862–1868.
- James Ravenscroft, Anika Oellrich, Shyamasree Saha, and Maria Liakata. 2016. Multi-label annotation in scientific articles-the multi-label cancer risk assessment corpus. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16)*, pages 4115–4123.
- Jason D Rennie, Lawrence Shih, Jaime Teevan, and David R Karger. 2003. Tackling the poor assumptions of naive bayes text classifiers. In *Proceedings of the 20th international conference on machine learning (ICML-03)*, pages 616–623.
- Patrick Ruch, Celia Boyer, Christine Chichester, Imad Tbahriti, Antoine Geissbühler, Paul Fabry, Julien Gobeill, Violaine Pillet, Dietrich Rebholz-Schuhmann, Christian Lovis, et al. 2007. Using argumentation to extract key sentences from biomedical abstracts. *International journal of medical informatics*, 76(2-3):195–200.
- Masashi Shimbo, Takahiro Yamasaki, and Yuji Matsumoto. 2003. Using sectioning information for text retrieval: a case study with the medline abstracts. In *Proceedings of Second International Workshop on Active Mining (AM’03)*.
- Eva Siegenthaler, Yves Bochud, Per Bergamin, and Pascal Wurtz. 2012. Reading on lcd vs e-ink displays: effects on fatigue and visual strain. *Ophthalmic and Physiological Optics*, 32(5):367–374.
- Amber C Stubbs. 2013. A methodology for using professional knowledge in corpus. *Waltham, MA: Brandeis University*.
- Simone Teufel and Marc Moens. 2002. Summarizing scientific articles: experiments with relevance and rhetorical status. *Computational linguistics*, 28(4):409–445.
- Simone Teufel et al. 1999. *Argumentative zoning: Information extraction from scientific text*. Ph.D. thesis, Citeseer.
- A. de Waard, S. Buckingham Shum, A. Carusi, J. Park, M. Samwald, and Á. Sándor. 2009. [Hypotheses, evidence and relationships: The hyper approach for representing scientific knowledge claims](#). In *Proceedings 8th International Semantic Web Conference, Workshop on Semantic Web Applications in Scientific Discourse. Lecture Notes in Computer Science*, Springer Verlag: Berlin.
- Anita de Waard and Henk Pander Maat. 2012. Verb form indicates discourse segment type in biological research papers: Experimental evidence. *Journal of English for Academic Purposes*, 11(4):357–366.
- Lucy Lu Wang, Kyle Lo, Yoganand Chandrasekhar, Russell Reas, Jiangjiang Yang, Darrin Eide, Kathryn Funk, Rodney Michael Kinney, Ziyang Liu, William Merrill, Paul Mooney, Dewey A. Murdick, Devvret Rishi, Jerry Sheehan, Zhihong Shen, Brandon Stilson, Alex D. Wade, Kuansan Wang, Christopher Wilhelm, Boya Xie, Douglas M. Raymond, Daniel S. Weld, Oren Etzioni, and Sebastian Kohlmeier. 2020. CORD-19: The covid-19 open research dataset. *ArXiv*, abs/2004.10706.
- Qingyun Wang, Lifu Huang, Zhiying Jiang, Kevin Knight, Heng Ji, Mohit Bansal, and Yi Luan. 2019. Paperrobot: Incremental draft generation of scientific ideas. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1980–1991.
- Derry Wijaya, Brendan Callahan, John Hewitt, Jie Gao, Xiao Ling, Marianna Apidianaki, and Chris Callison-Burch. 2017. [Learning translations via matrix completion](#). In *Conference on Empirical Methods in Natural Language Processing*, Copenhagen, Denmark.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, R’emi Louf, Morgan Funtowicz, and Jamie Brew. 2019. Huggingface’s transformers: State-of-the-art natural language processing. *ArXiv*, abs/1910.03771.
- Jian-Chen Wu, Yu-Chia Chang, Hsien-Chin Liou, and Jason S Chang. 2006. Computational analysis of move structures in academic abstracts. In *Proceedings of the COLING/ACL 2006 Interactive Presentation Sessions*, pages 41–44.
- Rui Yan, Mingkun Gao, Ellie Pavlick, and Chris Callison-Burch. 2014. [Are two heads better than one? crowdsourced translation via a two-step collaboration between translators and editors](#). In *The*

52nd Annual Meeting of the Association for Computational Linguistics, Baltimore, Maryland. Association for Computational Linguistics.

Omar F. Zaidan and Chris Callison-Burch. 2011. [Crowdsourcing translation: Professional quality from non-professionals](#). In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 1220–1229, Portland, Oregon, USA. Association for Computational Linguistics.

Haijun Zhai, Todd Lingren, Louise Deleger, Qi Li, Megan Kaiser, Laura Stoutenborough, and Imre Solti. 2013. [Web 2.0-based crowdsourcing for high-quality gold standard development in clinical natural language processing](#). *Journal of medical Internet research*, 15:e73.

Jin Zhao, Praveen Bysani, and Min-Yen Kan. 2012. [Exploiting classification correlations for the extraction of evidence-based practice information](#). In *AMIA Annual Symposium Proceedings*, volume 2012, page 1070. American Medical Informatics Association.