# Overview and Results: CL-SciSumm Shared Task 2019

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**Abstract.** The CL-SciSumm Shared Task is the first medium-scale shared task on scientific document summarization in the computational linguistics (CL) domain. In 2019, it comprised three tasks: (1A) identifying relationships between citing documents and the referred document, (1B) classifying the discourse facets, and (2) generating the abstractive summary. The dataset comprised 40 annotated sets of citing and reference papers of the CL-SciSumm 2018 corpus and 1000 more from the SciSumm-Net dataset. All papers are from the open access research papers in the CL domain. This overview describes the participation and the official results of the CL-SciSumm 2019 Shared Task, organized as a part of the $42^{nd}$ Annual Conference of the Special Interest Group in Information Retrieval (SIGIR), held in Paris, France in July 2019. We compare the participating systems in terms of two evaluation metrics and discuss the use of ROUGE as an evaluation metric. The annotated dataset used for this shared task and the scripts used for evaluation can be accessed and used by the community at: `https://github.com/WING-NUS/scisumm-corpus`.

## 1 Introduction

CL-SciSumm explores summarization of scientific research in the domain of computational linguistics research. It encourages the incorporation of new kinds of information in automatic scientific paper summarization, such as the facets of research information being summarized in the research paper. CL-SciSumm also encourages the use of citing mini-summaries written in other papers, by other scholars, when they refer to the paper. The Shared Task dataset comprises the set of citation sentences (i.e., “citances”) that reference a specific paper as a (community-created) summary of a topic or paper [19]. Citances for a reference paper are considered a synopses of its key points and also its key contributions and importance within an academic community [16]. The advantage of using citances is that they are embedded with meta-commentary and offer a contextual, interpretative layer to the cited text. Citances offer a view of the cited paper which could complement the reader’s context, possibly as a scholar [8].

The CL-SciSumm Shared Task is aimed at bringing together the summarization community to address challenges in scientific communication summarization. Over time, we anticipate that the Shared Task will spur the creation of new resources, tools and evaluation frameworks.

A pilot CL-SciSumm task was conducted at TAC 2014, as part of the larger BioMedSumm Task[4]. In 2016, a second CL-Scisumm Shared Task [6] was held as part of the Joint Workshop on Bibliometric-enhanced Information Retrieval and Natural Language Processing for Digital Libraries (BIRNDL) workshop [15] at the Joint Conference on Digital Libraries (JCDL 2016). This paper provides the results and insights from CL-SciSumm 2017, which was held as part of subsequent BIRNDL 2017 workshop[14] at the annual ACM Conference on Research and Development in Information Retrieval (SIGIR[5]).

## 2 Task

CL-SciSumm defined two serially dependent tasks that participants could attempt, given a canonical training and testing set of papers.

**Given**: A topic consists of a Reference Paper (RP) and ten or more Citing Papers (CPs) that all contain citations to the RP. In each CP, the text spans (i.e., citances) have been identified that pertain to a particular citation to the RP. Additionally, the dataset provides three types of summaries for each RP:

- the abstract, written by the authors of the research paper.
- the community summary, collated from the reference spans of its citances.
- a human-written summary, written by the annotators of the CL-SciSumm annotation effort.

**Task 1A**: For each citance, identify the spans of text (cited text spans) in the RP that most accurately reflect the citance. These are of the granularity of a sentence fragment, a full sentence, or several consecutive sentences (no more than 5).

**Task 1B**: For each cited text span, identify what facet of the paper it belongs to, from a predefined set of facets.

**Task 2**: Finally, generate a structured summary of the RP from the cited text spans of the RP. The length of the summary should not exceed 250 words. This was an optional bonus task.

## 3 Development

We built the CL-SciSumm corpus by randomly sampling research papers (Reference papers, RPs) from the ACL Anthology corpus and then downloading the

[4] http://www.nist.gov/tac/2014
[5] http://sigir.org/sigir2017/

citing papers (CPs) for those which had at least ten citations. The prepared dataset then comprised annotated citing sentences for a research paper, mapped to the sentences in the RP which they referenced. Summaries of the RP were also included.

The CL-SciSumm 2019 corpus consisted for 40 annotated RPs and their CPs. These are the same as described in our overview paper in CL-SciSumm 2018 [7]. The test set was blind. We reused the blind test we used for CL-SciSumm 2018 since we want to have a comparable evaluation CL-SciSumm 2019 systems that will have additional training data (see Section 3.1).

For details of the general procedure followed to construct the CL-SciSumm corpus, and changes made to the procedure in CL-SciSumm-2016, please see [6]. In 2017, we made revisions to the corpus to remove citances from passing citations. These are described in [5].

### 3.1 Annotation

The first annotated CL-SciSumm corpus was released for The CL-SciSumm 16 shared task. This was annotated based on annotation scheme from what was followed in previous editions of the task and the original BiomedSumm task developed by Cohen et. al[6]: Given each RP and its associated CPs, the annotation group was instructed to find citations to the RP in each CP. Specifically, the citation text, citation marker, reference text, and discourse facet were identified for each citation of the RP found in the CP.

Then CL-Scisumm-17 and CL-Scisumm-18 incrementally added more annotated RPs to its current size of 40 annotated RPs.

For CL-Scisumm-19, we augment this dataset both Task 1a and Task 2 so that they have approximately 1000 data points as opposed to 40 in previous years. Specifically, for Task 1, we used the method proposed by [17] to prepare noisy training data for about 1000 unannotated papers. This method involves automatically matching a citance in a CP with approximately similar reference spans in its RPs. The number of reference spans per citance is a hyperparameter that can set as input. For Task 2, we used the SciSummNet corpus proposed by [23].

## 4 Overview of Approaches

Nine systems out of the seventeen registered systems – in Task 1 and a subset of five also participated in Task 2 – submitted their output for evaluation. We include these system papers in the BIRNDL 2019 proceedings. We will now briefly summarise their methods and key results in lexicographic order by team name.

**System 1** is from Nanjing University of Science and Technology [13]. For Task 1A, they use multi-classifiers and integrate their results via voting system.

[6] http://www.nist.gov/tac/2014

Compared with previous work, this year they make new selection of features based on correlation analysis, apply similarity-based negative sampling strategy when creating training dataset and add deep learning models for classifications. For Task 1B, they firstly calculate the probability that each word would belong to the specific facet based on training corpus and then some prior rules are added to obtain final result. For Task 2, to obtain a logical summary, they group sentences in two ways, first based on their relevance between abstract segments and second arranged by recognized facet from task 1B. Then they pick out important sentences via ranking.

**System 2** is from Beijing University of Posts and Telecommunications (BUPT) [10]. They build a new feature of Word2vec_H for the CNN model to calculate sentence similarity for citation linkage. In addition to the methods used last year, they also intend to apply CNN for facet classification. In order to improve the performance of summarization, they develop more semantic representations for sentences based on neural network language models to construct new kernel matrix used in Determinantal Point Processes (DPPs).

**System 3** is from University of Manchester [24]. For Task 1 they looked into supervised and semi-supervised approaches. They explored the potential of fine-tuning bidirectional transformers for the identification of cited passages. They further formalised the task as a similarity ranking problem and implemented bilateral multi-perspective matching for natural language sentences. For Task 2, they used hybrid summarisation methods to create a summary from the content of the paper and the cited text spans.

**System 4** is from University of Toulouse [18]. They focus on Task 1A. They first identify candidate sentences in the reference paper and compute their similarities to the citing sentence using tf-idf and embedding-based methods as well as other features such as POS tags. They submitted 15 runs with different configurations.

**System 7** is from IIIT Hyderabad and Adobe Research [21]. Their architecture incorporates transfer learning by utilising a combination of pretrained embeddings which are subsequently used for building models for the given tasks. In particular, for task 1A, they locate the related text spans referred to by the citation text by creating paired text representations and employ pre-trained embedding mechanisms in conjunction with XGBoost, a gradient boosted decision tree algorithm to identify textual entailment. For task 1B, they make use of the same pretrained embeddings and use the RAKEL algorithm for multi-label classification.

**System 8** is from Universitat Pompeu Fabra and Universidad de la Republica [2]. They propose a supervised system based on recurrent neural networks and an unsupervised system based on sentence similarity for Task 1A, one supervised approach for Task 1B, and one supervised approach for Task 2. The approach for Task 2 follows the method by the winning approach in CL-SciSumm 2018.

**System 9** is from Politecnico di Torino [20]. Their approach to tasks 1A and 1B relies on an ensemble of classification and regression models trained on the annotated pairs of cited and citing sentences. Facet assignment is based on the relative positions of the cited sentences locally to the corresponding section and globally in the entire paper. Task 2 is addressed by predicting the overlap (in terms of units of text) between the selected text spans and the summary generated by the domain experts. The output summary consists of the subset of sentences maximizing the predicted overlap score.

**System 12** is from Nanjing University and Kim Il Sung University [9]. They propose a novel listwise ranking method for cited text identification. Their method have two stages: similarity-based ranking and supervised listwise ranking. In the first stage, we select the top-5 sentences per a citation text, due to the modified Jaccard similarity. These top-5 selected sentences are proceeded to rank by a CitedListNet (listwise ranking model based on deep learning). They select 36 similarity features and 11 section information as feature. Finally, they select two sentences on the sentence list ranked by CitedList- Net.

**System 17** is from National Technical University of Athens, Athens University of Economics and Business, and Athena Research and Innovation Center [4]. Their approach is twofold. Firstly they classify sentences of an abstract to predefined classes called "zones". They use sentences from selected zones to find the most similar ones of the rest sentences of the paper which constitute the "candidate sentences". Secondly, they employ a siamese bi-directional GRU neural network with a logistic regression layer to classify if a citation sentence cites a candidate sentence.

## 5 Evaluation

An automatic evaluation script was used to measure system performance for **Task 1A**, in terms of the sentence ID overlaps between the sentences identified in system output, versus the gold standard created by human annotators. The raw number of overlapping sentences were used to calculate the precision, recall and $F_1$ score for each system. We followed the approach in most SemEval tasks in reporting the overall system performance as its micro-averaged performance over all topics in the blind test set.

Additionally, we calculated lexical overlaps in terms of the ROUGE-2 and ROUGE-SU4 scores [11] between the system output and the human annotated gold standard reference spans.

We have been reporting ROUGE scoring since CL-SciSumm 17, for Tasks 1a and Task 2. Recall-Oriented Understudy for Gisting Evaluation (ROUGE) is a set of metrics used to automatically evaluate summarization systems [11] by measuring the overlap between computer-generated summaries and multiple human written reference summaries. In previous studies, ROUGE scores have significantly correlated with human judgments on summary quality [12]. Different variants of ROUGE differ according to the granularity at which overlap is calculated. For instance, ROUGE–2 measures the bigram overlap between the candidate computer-generated summary and the reference summaries. More generally, ROUGE–N measures the $n$-gram overlap. ROUGE–L measures the overlap in Longest Common Subsequence (LCS). ROUGE–S measures overlaps in skip-bigrams or bigrams with arbitrary gaps in-between. ROUGE-SU uses skip-bigram plus unigram overlaps. CL-SciSumm 2017 uses ROUGE-2 and ROUGE-SU4 for its evaluation.

**Task 1B** was evaluated as a proportion of the correctly classified discourse facets by the system, contingent on the expected response of Task 1A. As it is a multi-label classification, this task was also scored based on the precision, recall and $F_1$ scores.

**Task 2** was optional, and also evaluated using the ROUGE–2 and ROUGE–SU4 scores between the system output and three types of gold standard summaries of the research paper: the reference paper's abstract, a community summary, and a human summary.

The evaluation scripts have been provided at the CL-SciSumm Github repository[7] where the participants may run their own evaluation and report the results.

## 6 Results

This section compares the participating systems in terms of their performance. Five of the nine system that did Task 1 also did the bonus Task 2. Following are the plots with their performance measured by ROUGE–2 and ROUGE–SU4 against the 3 gold standard summary types. The results are provided in Table 1 and Figure 1. The detailed implementation of the individual runs are described in the system papers included in this proceedings volume.

For Task 1A, the best performance was shown by System 3 (Team UoM) [24]. Their performance was closely followed by System 12 [9]. Both teams implemented deep learning-based systems. One of the key goals of CL-SciSumm '19 was to boost performance of deep learning models by adding more training data. It is encouraging though not surprising to see the best performance from deep learning models. The third best system was system 2 (Team CIST-BUPT) which was also the best performer for Task 1B, the classification task. Second best performance Task 1B was by System 4 (Team IRIT-IRIS).

On the summarisation task, Task 2, System 3 (Team UoM) had the best performance against the abstract. System 2 (Team CIST-BUPT) had the best performance for community and human summaries. Again, both are deep learning-based systems. The additional 1000 summaries from SciSummnet as training data has resulted in the improved performance. System 2 was the second against abstract summaries, and system 3 was the second against human summaries.

## 7 Research questions and discussions

For CL-SciSumm '19, we augmented the CL-SciSumm '18 training datasets for both Task 1a and Task 2 so that they have approximately 1000 data points as

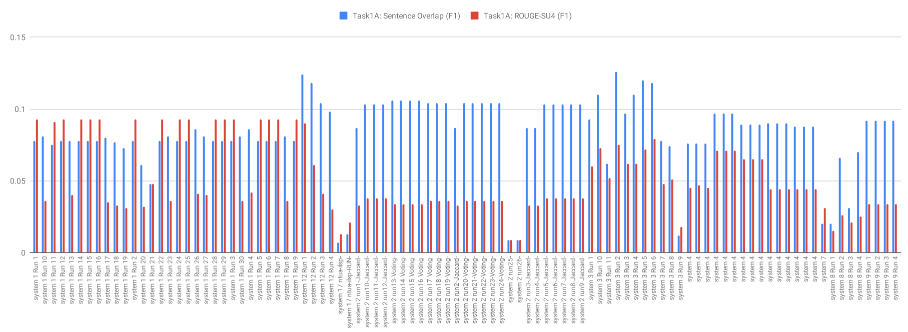
[7] github.com/WING-NUS/scisumm-corpus

| System | Task 1A: Sentence Overlap ($F_1$) | Task 1A: ROUGE-SU4 $F_1$ | Task 1B |
|---|---|---|---|
| system 3 Run 2 | 0.126 | 0.075 | 0.312 |
| system 12 Run 1 | 0.124 | 0.090 | 0.221 |
| system 3 Run 5 | 0.120 | 0.072 | 0.303 |
| system 3 Run 6 | 0.118 | 0.079 | 0.292 |
| system 12 Run 2 | 0.118 | 0.061 | 0.266 |
| system 3 Run 10 | 0.110 | 0.073 | 0.276 |
| system 3 Run 4 | 0.110 | 0.062 | 0.283 |
| system 2 run15-Voting-1.1-SubtitleAndHfw-QD_method_1 | 0.106 | 0.034 | 0.389 |
| system 2 run13-Voting-1.1-SubtitleAndHfw-LSA_method_3 | 0.106 | 0.034 | 0.389 |
| system 2 run14-Voting-1.1-SubtitleAndHfw-LSA_method_4 | 0.106 | 0.034 | 0.389 |
| system 2 run16-Voting-1.1-SubtitleAndHfw-SentenceVec_method_2 | 0.106 | 0.034 | 0.389 |
| system 2 run23-Voting-2.0-Voting-QD_method_1 | 0.104 | 0.036 | 0.341 |
| system 2 run24-Voting-2.0-Voting-SentenceVec_method_2 | 0.104 | 0.036 | 0.341 |
| system 2 run20-Voting-2.0-TextCNN-SentenceVec_method_2 | 0.104 | 0.036 | 0.342 |
| system 2 run21-Voting-2.0-Voting-LSA_method_3 | 0.104 | 0.036 | 0.341 |
| system 2 run18-Voting-2.0-TextCNN-LSA_method_4 | 0.104 | 0.036 | 0.342 |
| system 2 run22-Voting-2.0-Voting-LSA_method_4 | 0.104 | 0.036 | 0.341 |
| system 2 run19-Voting-2.0-TextCNN-QD_method_1 | 0.104 | 0.036 | 0.342 |
| system 2 run17-Voting-2.0-TextCNN-LSA_method_3 | 0.104 | 0.036 | 0.342 |
| system 12 Run 3 | 0.104 | 0.041 | 0.286 |
| system 2 run10-Jaccard-Focused-Voting-LSA_method_4 | 0.103 | 0.038 | 0.294 |
| system 2 run7-Jaccard-Focused-SubtitleAndHfw-QD_method_1 | 0.103 | 0.038 | 0.385 |
| system 2 run5-Jaccard-Focused-SubtitleAndHfw-LSA_method_3 | 0.103 | 0.038 | 0.385 |
| system 2 run9-Jaccard-Focused-Voting-LSA_method_3 | 0.103 | 0.038 | 0.294 |
| system 2 run12-Jaccard-Focused-Voting-SentenceVec_method_2 | 0.103 | 0.038 | 0.294 |
| system 2 run6-Jaccard-Focused-SubtitleAndHfw-LSA_method_4 | 0.103 | 0.038 | 0.385 |
| system 2 run11-Jaccard-Focused-Voting-QD_method_1 | 0.103 | 0.038 | 0.294 |
| system 2 run8-Jaccard-Focused-SubtitleAndHfw-SentenceVec_method_2 | 0.103 | 0.038 | 0.385 |
| system 12 Run 4 | 0.098 | 0.030 | 0.315 |
| system 3 Run 3 | 0.097 | 0.062 | 0.251 |
| system 4 WithoutEmb_Training20182019_Test2019_3_0.1 | 0.097 | 0.071 | 0.286 |
| system 4 WithoutEmb_Training2018_Test2019_3_0.1 | 0.097 | 0.071 | 0.286 |
| system 4 WithoutEmb_Training2019_Test2019_3_0.1 | 0.097 | 0.071 | 0.286 |
| system 3 Run 1 | 0.093 | 0.060 | 0.255 |
| system 9 Run 2 | 0.092 | 0.034 | 0.229 |
| system 9 Run 3 | 0.092 | 0.034 | 0.229 |
| system 9 Run 1 | 0.092 | 0.034 | 0.229 |
| system 9 Run 4 | 0.092 | 0.034 | 0.229 |
| system 4 WithoutEmbTopsim_Training20182019_Test2019_0.15_5_0.05 | 0.090 | 0.044 | 0.351 |
| system 4 WithoutEmbTopsim_Training2019_Test2019_0.15_5_0.05 | 0.090 | 0.044 | 0.351 |
| system 4 WithoutEmbTopsim_Training2018_Test2019_0.15_5_0.05 | 0.090 | 0.044 | 0.351 |
| system 4 WithoutEmbPOS_Training20182019_Test2019_3_0.1 | 0.089 | 0.065 | 0.263 |
| system 4 WithoutEmbPOS_Training2019_Test2019_3_0.1 | 0.089 | 0.065 | 0.263 |
| system 4 WithoutEmbPOS_Training2018_Test2019_3_0.1 | 0.089 | 0.065 | 0.263 |
| system 4 WithoutEmbTopsimPOS_Training2019_Test2019_0.15_5_0.05 | 0.088 | 0.044 | 0.346 |
| system 4 WithoutEmbTopsimPOS_Training2018_Test2019_0.15_5_0.05 | 0.088 | 0.044 | 0.346 |
| system 4 WithoutEmbTopsimPOS_Training20182019_Test2019_0.15_5_0.05 | 0.088 | 0.044 | 0.346 |
| system 2 run1-Jaccard-Cascade-Voting-LSA_method_3 | 0.087 | 0.033 | 0.274 |
| system 2 run3-Jaccard-Cascade-Voting-QD_method_1 | 0.087 | 0.033 | 0.274 |
| system 2 run4-Jaccard-Cascade-Voting-SentenceVec_method_2 | 0.087 | 0.033 | 0.274 |
| system 2 run2-Jaccard-Cascade-Voting-LSA_method_4 | 0.087 | 0.033 | 0.274 |
| system 1 Run 26 | 0.086 | 0.041 | 0.245 |
| system 1 Run 4 | 0.086 | 0.042 | 0.241 |
| system 1 Run 30 | 0.081 | 0.036 | 0.242 |
| system 1 Run 27 | 0.081 | 0.040 | 0.207 |
| system 1 Run 8 | 0.081 | 0.036 | 0.242 |
| system 1 Run 10 | 0.081 | 0.036 | 0.242 |
| system 1 Run 23 | 0.081 | 0.036 | 0.242 |
| system 1 Run 17 | 0.080 | 0.035 | 0.236 |
| system 3 Run 7 | 0.078 | 0.048 | 0.218 |
| system 1 Run 12 | 0.078 | 0.093 | 0.098 |
| system 1 Run 15 | 0.078 | 0.093 | 0.110 |
| system 1 Run 28 | 0.078 | 0.093 | 0.098 |
| system 1 Run 2 | 0.078 | 0.093 | 0.110 |
| system 1 Run 9 | 0.078 | 0.093 | 0.110 |
| system 1 Run 25 | 0.078 | 0.093 | 0.098 |
| system 1 Run 13 | 0.078 | 0.040 | 0.205 |
| system 1 Run 24 | 0.078 | 0.093 | 0.110 |
| system 1 Run 22 | 0.078 | 0.093 | 0.098 |
| system 1 Run 3 | 0.078 | 0.093 | 0.098 |
| system 1 Run 5 | 0.078 | 0.093 | 0.113 |
| system 1 Run 6 | 0.078 | 0.093 | 0.110 |
| system 1 Run 1 | 0.078 | 0.093 | 0.113 |
| system 1 Run 14 | 0.078 | 0.093 | 0.113 |
| system 1 Run 7 | 0.078 | 0.093 | 0.098 |
| system 1 Run 16 | 0.078 | 0.093 | 0.098 |
| system 1 Run 29 | 0.078 | 0.093 | 0.110 |
| system 1 Run 18 | 0.077 | 0.033 | 0.232 |
| system 4 unweightedPOS_W2v_Training2018_Test2019_3_0.05 | 0.076 | 0.045 | 0.201 |
| system 4 unweightedPOS_W2v_Training20182019_Test2019_3_0.05 | 0.076 | 0.047 | 0.201 |
| system 4 unweightedPOS_W2v_Training2019_Test2019_3_0.05 | 0.076 | 0.045 | 0.201 |
| system 1 Run 11 | 0.075 | 0.091 | 0.106 |
| system 3 Run 8 | 0.074 | 0.051 | 0.221 |
| system 1 Run 19 | 0.073 | 0.031 | 0.218 |
| system 8 Run 4 | 0.070 | 0.025 | 0.122 |
| system 8 Run 2 | 0.066 | 0.026 | 0.277 |
| system 3 Run 11 | 0.062 | 0.052 | 0.150 |
| system 1 Run 20 | 0.061 | 0.032 | 0.178 |
| system 1 Run 21 | 0.048 | 0.048 | 0.083 |
| system 8 Run 3 | 0.031 | 0.021 | 0.078 |
| system 8 Run 1 | 0.020 | 0.015 | 0.070 |
| system 7 | 0.020 | 0.031 | 0.045 |
| system 17 ntua-ilsp-RUN-NNT | 0.013 | 0.021 | 0.016 |
| system 3 Run 9 | 0.012 | 0.018 | 0.039 |
| system 2 run25-Word2vec-H-CNN-SubtitleAndHfw-QD_method_1 | 0.009 | 0.009 | 0.047 |
| system 2 run26-Word2vec-H-CNN-SubtitleAndHfw-SentenceVec_method_2 | 0.009 | 0.009 | 0.047 |
| system 17 ntua-ilsp-RUN_NNF | 0.007 | 0.013 | 0.013 |

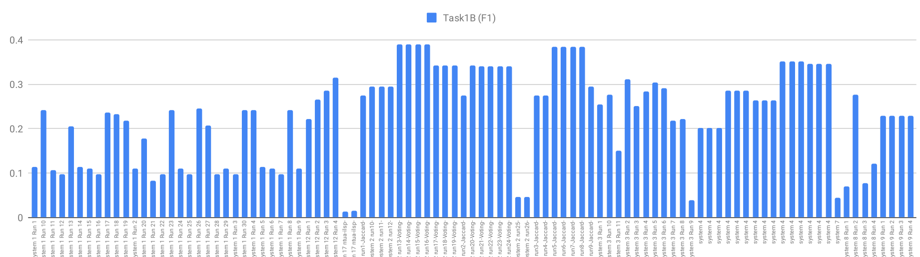
Table 1: Systems' performance in Task 1A and 1B, ordered by their $F_1$-scores for sentence overlap on Task 1A. Each system's rank by their performance on ROUGE on Task 1A and 1B are shown in parentheses.

| System | Vs. Abstract | | Vs. Community | | Vs. Human | |
|---|---|---|---|---|---|---|
| | **R–2** | **RSU–4** | **R–2** | **RSU–4** | **R–2** | **RSU–4** |
| system 3 Run 1 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 3 Run 11 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 3 Run 6 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 3 Run 2 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 3 Run 7 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 3 Run 10 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 3 Run 8 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 3 Run 5 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 3 Run 3 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 3 Run 4 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 3 Run 9 | 0.514 | 0.295 | 0.106 | 0.062 | 0.265 | 0.180 |
| system 2 run3-Jaccard-Cascade-Voting-QD_method_1_human | 0.389 | 0.210 | 0.122 | 0.063 | 0.278 | 0.200 |
| system 2 run3-Jaccard-Cascade-Voting-QD_method_1_abstract | 0.389 | 0.210 | 0.122 | 0.063 | 0.278 | 0.200 |
| system 2 run23-Voting-2.0-Voting-QD_method_1_human | 0.386 | 0.227 | 0.121 | 0.063 | 0.257 | 0.189 |
| system 2 run19-Voting-2.0-TextCNN-QD_method_1_human | 0.386 | 0.227 | 0.121 | 0.063 | 0.257 | 0.189 |
| system 2 run19-Voting-2.0-TextCNN-QD_method_1_abstract | 0.386 | 0.227 | 0.121 | 0.063 | 0.257 | 0.189 |
| system 2 run23-Voting-2.0-Voting-QD_method_1_abstract | 0.386 | 0.227 | 0.121 | 0.063 | 0.257 | 0.189 |
| system 2 run15-Voting-1.1-SubtitleAndHfw-QD_method_1_human | 0.381 | 0.211 | 0.119 | 0.062 | 0.267 | 0.191 |
| system 2 run15-Voting-1.1-SubtitleAndHfw-QD_method_1_abstract | 0.381 | 0.211 | 0.119 | 0.062 | 0.267 | 0.191 |
| system 2 run10-Jaccard-Focused-Voting-LSA_method_4_community | 0.368 | 0.186 | 0.096 | 0.053 | 0.252 | 0.170 |
| system 2 run2-Jaccard-Cascade-Voting-LSA_method_4_community | 0.368 | 0.186 | 0.096 | 0.053 | 0.252 | 0.170 |
| system 2 run18-Voting-2.0-TextCNN-LSA_method_4_community | 0.368 | 0.186 | 0.096 | 0.053 | 0.252 | 0.170 |
| system 2 run6-Jaccard-Focused-SubtitleAndHfw-LSA_method_4_community | 0.368 | 0.186 | 0.096 | 0.053 | 0.252 | 0.170 |
| system 2 run14-Voting-1.1-SubtitleAndHfw-LSA_method_4_community | 0.368 | 0.186 | 0.096 | 0.053 | 0.252 | 0.170 |
| system 2 run22-Voting-2.0-Voting-LSA_method_4_community | 0.368 | 0.186 | 0.096 | 0.053 | 0.252 | 0.170 |
| system 2 run11-Jaccard-Focused-Voting-QD_method_1_human | 0.367 | 0.201 | 0.121 | 0.062 | 0.258 | 0.184 |
| system 2 run7-Jaccard-Focused-SubtitleAndHfw-QD_method_1_abstract | 0.367 | 0.201 | 0.121 | 0.062 | 0.258 | 0.184 |
| system 2 run11-Jaccard-Focused-Voting-QD_method_1_abstract | 0.367 | 0.201 | 0.121 | 0.062 | 0.258 | 0.184 |
| system 2 run7-Jaccard-Focused-SubtitleAndHfw-QD_method_1_human | 0.367 | 0.201 | 0.121 | 0.062 | 0.258 | 0.184 |
| system 9 Run 1 | 0.364 | 0.196 | 0.196 | 0.104 | 0.218 | 0.144 |
| system 9 Run 3 | 0.359 | 0.194 | 0.195 | 0.104 | 0.211 | 0.141 |
| system 9 Run 2 | 0.346 | 0.176 | 0.209 | 0.112 | 0.215 | 0.140 |
| system 2 run5-Jaccard-Focused-SubtitleAndHfw-LSA_method_3_community | 0.343 | 0.171 | 0.097 | 0.049 | 0.254 | 0.174 |
| system 2 run13-Voting-1.1-SubtitleAndHfw-LSA_method_3_community | 0.343 | 0.171 | 0.097 | 0.049 | 0.254 | 0.174 |
| system 2 run1-Jaccard-Cascade-Voting-LSA_method_3_community | 0.343 | 0.171 | 0.097 | 0.049 | 0.254 | 0.174 |
| system 2 run9-Jaccard-Focused-Voting-LSA_method_3_community | 0.343 | 0.171 | 0.097 | 0.049 | 0.254 | 0.174 |
| system 2 run21-Voting-2.0-Voting-LSA_method_3_community | 0.343 | 0.171 | 0.097 | 0.049 | 0.254 | 0.174 |
| system 2 run17-Voting-2.0-TextCNN-LSA_method_3_community | 0.343 | 0.171 | 0.097 | 0.049 | 0.254 | 0.174 |
| system 9 Run 4 | 0.340 | 0.174 | 0.206 | 0.111 | 0.208 | 0.138 |
| system 8 Run 1 | 0.329 | 0.172 | 0.149 | 0.090 | 0.241 | 0.171 |
| system 2 run12-Jaccard-Focused-Voting-SentenceVec_method_2_abstract | 0.318 | 0.171 | 0.142 | 0.075 | 0.239 | 0.167 |
| system 2 run12-Jaccard-Focused-Voting-SentenceVec_method_2_human | 0.318 | 0.171 | 0.142 | 0.075 | 0.239 | 0.167 |
| system 2 run8-Jaccard-Focused-SubtitleAndHfw-SentenceVec_method_2_abstract | 0.318 | 0.171 | 0.142 | 0.075 | 0.239 | 0.167 |
| system 2 run8-Jaccard-Focused-SubtitleAndHfw-SentenceVec_method_2_human | 0.318 | 0.171 | 0.142 | 0.075 | 0.239 | 0.167 |
| system 8 Run 2 | 0.316 | 0.167 | 0.169 | 0.101 | 0.245 | 0.169 |
| system 8 Run 3 | 0.311 | 0.156 | 0.153 | 0.093 | 0.252 | 0.170 |
| system 2 run20-Voting-2.0-TextCNN-SentenceVec_method_2_abstract | 0.296 | 0.152 | 0.128 | 0.067 | 0.252 | 0.177 |
| system 2 run24-Voting-2.0-Voting-SentenceVec_method_2_human | 0.296 | 0.152 | 0.128 | 0.067 | 0.252 | 0.177 |
| system 2 run20-Voting-2.0-TextCNN-SentenceVec_method_2_human | 0.296 | 0.152 | 0.128 | 0.067 | 0.252 | 0.177 |
| system 2 run24-Voting-2.0-Voting-SentenceVec_method_2_abstract | 0.296 | 0.152 | 0.128 | 0.067 | 0.252 | 0.177 |
| system 1 Run 26 | 0.296 | 0.145 | 0.193 | 0.108 | 0.224 | 0.150 |
| system 1 Run 4 | 0.294 | 0.144 | 0.191 | 0.108 | 0.235 | 0.151 |
| system 2 run4-Jaccard-Cascade-Voting-SentenceVec_method_2_abstract | 0.287 | 0.155 | 0.121 | 0.066 | 0.247 | 0.175 |
| system 2 run4-Jaccard-Cascade-Voting-SentenceVec_method_2_human | 0.287 | 0.155 | 0.121 | 0.066 | 0.247 | 0.175 |
| system 2 run16-Voting-1.1-SubtitleAndHfw-SentenceVec_method_2_human | 0.277 | 0.150 | 0.124 | 0.064 | 0.246 | 0.179 |
| system 2 run16-Voting-1.1-SubtitleAndHfw-SentenceVec_method_2_abstract | 0.277 | 0.150 | 0.124 | 0.064 | 0.246 | 0.179 |
| system 2 run25-Word2vec-H-CNN-SubtitleAndHfw-QD_method_1_abstract | 0.277 | 0.158 | 0.115 | 0.059 | 0.238 | 0.167 |
| system 2 run25-Word2vec-H-CNN-SubtitleAndHfw-QD_method_1_human | 0.277 | 0.158 | 0.115 | 0.059 | 0.238 | 0.167 |
| system 1 Run 8 | 0.277 | 0.137 | 0.200 | 0.115 | 0.229 | 0.151 |
| system 1 Run 30 | 0.276 | 0.137 | 0.204 | 0.117 | 0.237 | 0.154 |
| system 1 Run 10 | 0.276 | 0.137 | 0.204 | 0.117 | 0.237 | 0.154 |
| system 1 Run 18 | 0.262 | 0.127 | 0.196 | 0.113 | 0.223 | 0.149 |
| system 2 run26-Word2vec-H-CNN-SubtitleAndHfw-SentenceVec_method_2_human | 0.261 | 0.145 | 0.126 | 0.066 | 0.222 | 0.153 |
| system 2 run26-Word2vec-H-CNN-SubtitleAndHfw-SentenceVec_method_2_abstract | 0.261 | 0.145 | 0.126 | 0.066 | 0.222 | 0.153 |
| system 8 Run 4 | 0.246 | 0.147 | 0.131 | 0.084 | 0.170 | 0.141 |
| system 1 Run 20 | 0.239 | 0.122 | 0.177 | 0.102 | 0.231 | 0.158 |
| system 2 run15-Voting-1.1-SubtitleAndHfw-QD_method_1_community | 0.207 | 0.123 | 0.126 | 0.070 | 0.215 | 0.153 |
| system 2 run3-Jaccard-Cascade-Voting-QD_method_1_community | 0.205 | 0.118 | 0.130 | 0.069 | 0.201 | 0.144 |
| system 2 run4-Jaccard-Cascade-Voting-SentenceVec_method_2_community | 0.204 | 0.123 | 0.140 | 0.077 | 0.221 | 0.159 |
| system 2 run24-Voting-2.0-Voting-SentenceVec_method_2_community | 0.203 | 0.126 | 0.138 | 0.076 | 0.225 | 0.164 |
| system 2 run20-Voting-2.0-TextCNN-SentenceVec_method_2_community | 0.203 | 0.126 | 0.138 | 0.076 | 0.225 | 0.164 |
| system 2 run8-Jaccard-Focused-SubtitleAndHfw-SentenceVec_method_2_community | 0.199 | 0.115 | 0.131 | 0.073 | 0.222 | 0.156 |
| system 2 run16-Voting-1.1-SubtitleAndHfw-SentenceVec_method_2_community | 0.199 | 0.116 | 0.131 | 0.071 | 0.207 | 0.156 |
| system 2 run12-Jaccard-Focused-Voting-SentenceVec_method_2_community | 0.199 | 0.115 | 0.131 | 0.073 | 0.222 | 0.156 |
| system 2 run19-Voting-2.0-TextCNN-QD_method_1_community | 0.198 | 0.114 | 0.135 | 0.072 | 0.226 | 0.156 |
| system 2 run23-Voting-2.0-Voting-QD_method_1_community | 0.198 | 0.114 | 0.135 | 0.072 | 0.226 | 0.156 |
| system 2 run11-Jaccard-Focused-Voting-QD_method_1_community | 0.197 | 0.108 | 0.134 | 0.069 | 0.220 | 0.154 |
| system 2 run7-Jaccard-Focused-SubtitleAndHfw-QD_method_1_community | 0.197 | 0.108 | 0.134 | 0.069 | 0.220 | 0.154 |
| system 1 Run 12 | 0.184 | 0.111 | 0.192 | 0.110 | 0.194 | 0.151 |
| system 1 Run 2 | 0.183 | 0.111 | 0.192 | 0.112 | 0.193 | 0.150 |
| system 1 Run 6 | 0.183 | 0.111 | 0.192 | 0.112 | 0.193 | 0.150 |
| system 1 Run 14 | 0.183 | 0.112 | 0.192 | 0.112 | 0.193 | 0.150 |
| system 2 run26-Word2vec-H-CNN-SubtitleAndHfw-SentenceVec_method_2_community | 0.180 | 0.106 | 0.112 | 0.063 | 0.211 | 0.147 |
| system 1 Run 28 | 0.167 | 0.104 | 0.192 | 0.108 | 0.194 | 0.150 |
| system 1 Run 22 | 0.167 | 0.104 | 0.192 | 0.108 | 0.194 | 0.150 |
| system 1 Run 16 | 0.167 | 0.104 | 0.192 | 0.108 | 0.194 | 0.150 |
| system 1 Run 24 | 0.166 | 0.104 | 0.193 | 0.109 | 0.194 | 0.150 |
| system 2 run25-Word2vec-H-CNN-SubtitleAndHfw-QD_method_1_community | 0.151 | 0.097 | 0.126 | 0.069 | 0.201 | 0.138 |
| system 1 Run 13 | 0.144 | 0.077 | 0.148 | 0.087 | 0.146 | 0.111 |
| system 1 Run 17 | 0.119 | 0.063 | 0.149 | 0.095 | 0.128 | 0.098 |
| system 1 Run 11 | 0.114 | 0.066 | 0.145 | 0.088 | 0.099 | 0.085 |
| system 1 Run 5 | 0.112 | 0.067 | 0.136 | 0.085 | 0.140 | 0.103 |
| system 1 Run 27 | 0.110 | 0.064 | 0.136 | 0.089 | 0.142 | 0.098 |
| system 1 Run 25 | 0.107 | 0.061 | 0.145 | 0.092 | 0.113 | 0.086 |
| system 1 Run 1 | 0.107 | 0.061 | 0.156 | 0.096 | 0.139 | 0.098 |
| system 1 Run 15 | 0.105 | 0.062 | 0.128 | 0.080 | 0.097 | 0.077 |
| system 1 Run 9 | 0.101 | 0.063 | 0.147 | 0.091 | 0.121 | 0.091 |
| system 1 Run 29 | 0.093 | 0.057 | 0.139 | 0.086 | 0.120 | 0.093 |
| system 1 Run 19 | 0.091 | 0.056 | 0.157 | 0.083 | 0.113 | 0.085 |
| system 1 Run 23 | 0.090 | 0.058 | 0.165 | 0.094 | 0.108 | 0.084 |
| system 1 Run 3 | 0.089 | 0.051 | 0.146 | 0.084 | 0.116 | 0.088 |
| system 1 Run 7 | 0.082 | 0.050 | 0.162 | 0.096 | 0.121 | 0.095 |
| system 1 Run 21 | 0.075 | 0.050 | 0.109 | 0.063 | 0.121 | 0.083 |

Table 2: Systems' performance for Task 2 ordered by their ROUGE–2(R–2) and ROUGE–SU4(R–SU4) $F_1$-scores. Each system's rank by their performance on the corresponding evaluation is shown in parentheses. Winning scores are bolded.

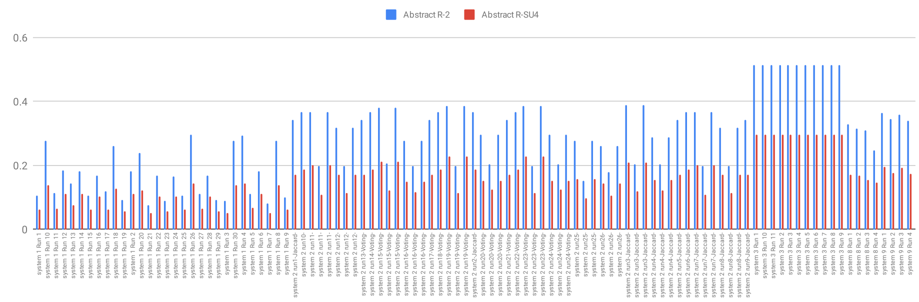



(a)

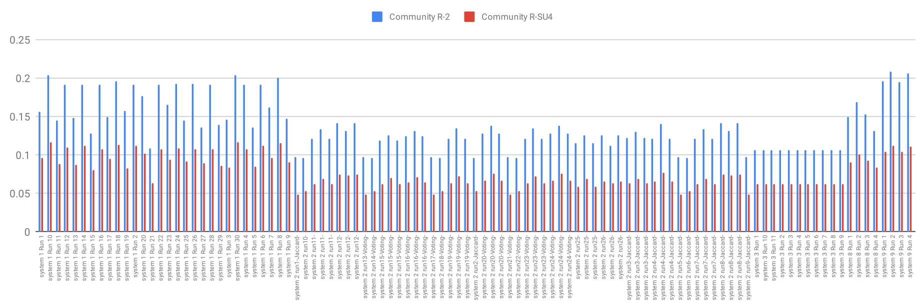



(b)

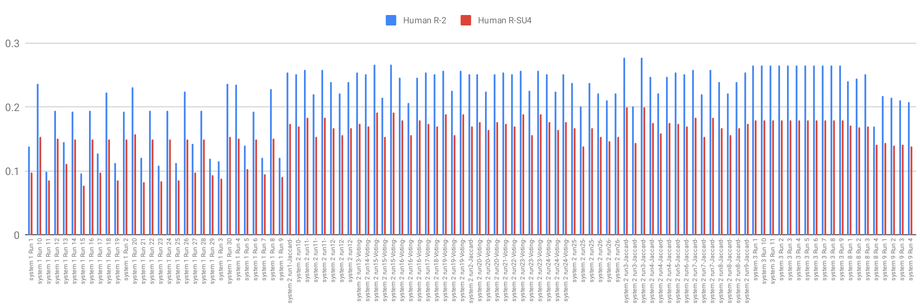
Fig. 1: Performances on (a) Task 1A in terms of sentence overlap and ROUGE-SU4, and (b) Task 1B conditional on Task 1A




(a)




(b)




(c)

Fig. 2: Task 2 Performances on (a) Abstract, (b) Community and (c) Human summaries. Plots correspond to the numbers in Table 2.

opposed to 40 in previous years. Specifically, for Task 1, we used the method proposed by [17] to prepare noisy training data for about 1000 unannotated papers; for Task 2, we used the SciSummNet corpus proposed by [23]. For CL-SciSumm '19 we use the same blind test data used in CL-SciSumm '18.

Based on this we propose the following research questions to comparatively analyse results from CL-SciSumm '18 with those from CL-SciSumm '19. The research questions we have are:

**RQ1.** Did data augmentation help systems achieve better performance?
The best Task 1a performance (sentence overlap $F_1$) this year is 0.126 from System 3 [24] which is a deep learning system trained on augmented data. This is about 0.02 lower than the best CL-SciSumm'18 system [22] which was at 0.145. It appears that the data augmentation has helped deep learning methods. The only fully deep learning system from CL-SciSumm '18 [3] achieved 0.044. So, increasing training data is clearly the way forward. Traditional machine learning based systems such as [10] seem to suffer from noise in the augmented data. We propose to use better data generation method that produces data cleaner than the naive similarity based cut-off method [17] used this time.

Note that there was no data augmentation to Task 1b. So, the performance of traditional methods across CL-SciSumm '18 and CL-SciSumm, '19 are largely the same.

The best on CL-SciSumm '19 Task 2 performance on human written summaries on ROUGE-2 is 0.278 by [10]. This is higher than the best CL-SciSumm'18 system which score 0.252 [1]. This suggests that the additional 1000 ScisummNet summaries is useful to further performance. It also indicates that SciSummNet relatively cleaner than the auto annotated data used for Task 1a.

**RQ2.** CL-SciSumm '19 encouraged participants to use deep learning based methods; do they perform better than traditional machine learning methods?
In Task 1a the best performing CL-SciSumm '19 system The best performing CL-SciSumm '18 system [22] used traditional models including random forests and ranking models trained on the CL-SciSumm '18 training data. This implies that for Task 1a, traditional models trained on clean data perform better than deep learning models trained on noisy data. However, if we look at CL-SciSumm '19 systems' performances, we notice that deep learning models perform better than traditional machine learning models when trained on the augmented data.

On Task 1b, systems using traditional methods perform better than deep learning systems. Note that the winner for Task 1a, System 3, is not the best system for Task 1b although they are not far behind. We also did not add any additional training data to Task 1b. So, we cannot rule out that deep learning systems will not perform better than traditional methods when trained on enough data.

On Task 2, the best performing system on human summaries, System 2, using neural representations trained on the 1000 plus summaries, does the best with a ROUGE-2 score of 0.278. This is higher than CL-SciSumm '18 top system using traditional methods. System 3, the second best Cl-SciSumm '19 system an end-end deep learning model, with a score of 0.265 is also higher than CLSciSumm

’18 top system. With a score of 0.514 System 3 also improves the state-of-the-art agasint abstracts by 0.2 on ROUGE-2 score. System 3 is also the top system on community summaries with a ROUGE-2 score of 0.204.

In summary, deep learning models do well across the board for summaries. Traditional methods do better on Task 1a on small but clean training data. Deep learning methods take over on large bu tnoisy data.

## 8 Conclusion

Nine systems participated in CL-SciSumm 2019 shared tasks. The systems were provided with larger but noisy corpus with automatic annotation. Nearly all the teams had neural methods and many employed transfer learning. Participants also experimented with the use of word embeddings trained on the shared task corpus, as well as on other domain corpora. We found that data augmentation for Task 1a may have helped deep learning models but not traditional machine learning methods. It also appears that deep learning methods perform better than traditional methods across the board when they have enough training data. We will explore methods to obtain cleaner training data for Task 1 without or with minimal human annotation effort.

We recommend that future approaches should go beyond off-the-shelf deep learning methods, and also exploit the structural and semantic characteristics that are unique to scientific documents; perhaps as an enrichment device for word embeddings. The committee also observes that CL-SciSumm series over the past 5 years has catalysed research in the area of scientific document summarisation. We observe that a number of papers outside of the BIRNDL workshop published at prominent NLP and IR venues evaluate on the CL-SciSumm gold standard data. To create a reference corpus for the task was a key goal of the series. We have achieved this goal now. We will consider newer tasks to push the effort towards automated literature reviews. We will also consider switching the format of the shared evaluation from a shared task to a leaderboard to which systems can submit evaluations asynchronously throughout the year.

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