CBNU at TREC 2019 Incident Streams Track

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ABSTRACT

This paper describes the participation of the CBNU team at the TREC Incident Streams Track 2019 [1]. Our approach is the same with CBNU at TREC-IS 2018 [2]. In our participation to TREC-IS Track 2018 and 2019, we focus on the conceptual representation for crisis-related terms. In order to classify a stream of tweets related to the incident, the terms in each tweet are represented as conceptual entities such as event entities, category indicator entities, information type entities, URL entities, and user entities. For tweet classification, we have compared support vector machines (SVM) and convolutional neural networks (CNNs).

1. SUBMITTED RUNS

The submitted runs are described as follows.

- cbnuS1: SVMs with Conceptual Representation
- cbnuC1: Convolutional Neural Networks (CNNs) with Conceptual Representation

2. RESULTS

The experimental results of alerting performance and information type categorization are shown in Table 1 and Table 2, respectively. Table 2 shows results of the information priority level.

Table 1. Results for Alerting Performance

Run ID	High Importance Alert Worth	Low Importance Alert Worth	Accumulated Importance Alert Worth
cbnuS1	0.2938	-0.5548	-0.1305
cbnuC1	0.2938	-0.5548	-0.1305
Median	*-0.9197*	-	*-0.4609*

Table 2. Results for Information Type Categorization (in Accuracy)

Run ID	Information Type	High Importance Information Type	Low Importance Information Type
cbnuS1	0.8788	0.9759	0.8481
cbnuC1	0.8788	0.9759	0.8481
Median	0.8583	-	-

Table 3. Results for Information Priority Level

Run ID	Priority Estimation Error	Priority Estimation Error High Importance	Priority Estimation Error Low Importance
cbnuS1	0.2930	0.1468	0.3392
cbnuC1	0.2930	0.1468	0.3392
Median	*0.1028*	*0.1767*	-

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