CBNU at TREC 2018 Incident Streams Track

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ABSTRACT

This paper describes the participation of the CBNU team at the TREC Incident Streams Track 2018. For tweet representation, crisis-related terms are represented as conceptual entities. For tweet classification, we have compared support vector machines and our deep learning model which combines class activation mapping with one-shot learning in convolutional neural networks.

Keywords
Conceptual representation, Incident Streams, Convolutional neural networks, Class activation mapping, One-shot learning

1. INTRODUCTION

TREC Incident Streams Track (TREC-IS) 2018 is a task for participant systems to categorize the tweets in each event/incident's stream by information type in order to automatically process social media streams during emergency situations [1]. In our participation to TREC-IS Track 2018, we focus on conceptual representation for crisis-related terms and combining deep learning models for information type classification.

2. Conceptual Representation for Crisis-Related Tweets

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.

2.1 Event Entities

In TREC-IS training data, hashtags and keywords used for collecting a stream of tweets related to each incident have been provided. For conceptual representation, the hashtags and keywords are represented as event entities: <EventLoc>, <EventCri>, and <EventClu> according to the information in such as a location, an incident and a clue. The followings are examples of event entity representation for each hashtag or keyword.

- #COfire: <EventLoc>, <EventCri>
- LAX shooting: <EventLoc>, <EventCri>
- #Philippines: <EventLoc>
- sismo: <EventCri>
- #StrongerPH: <EventClu>

2.2 Category Indicator Entities

In a training data, category indicator terms are provided for each tweet by human assessors. We have used the indicator terms for each category indicator entity. The number of categories in TREC-IS and category indicator entities are 25 such as <InformationWanted>, <ServiceAvailable>, <Official> and etc.

The followings are examples of category indicator entity representation for each term.

- <InformationWanted>: does anyone know, report?, what is going on, …
- <ServiceAvailable>: heavy air tanker, animal hospital, offering housing, …
- <Official>: tsunami warning issued, briefing, emergency declaration, …

The terms for 5 category indicator entities such as volunteering, donation, multimedia, and sentiment are expanded using terms in thesaurus.com and relatedwords.org.

2.3 Information Type Entities

In order to represent information type for each term, information type entities are defined as followings:

<Question>, <Communication>, <Organization>, <Evacuation>, <Location>, <Emergency>, <Person1st>, <Informal>, <Emotion/reaction>, <Narration>, <News>, <Disaster/threat>, <Change>, <Service>, <Provider>, <Fact>, <Unit>, <Government>, <Advice>, <Pastdate>, <Pastverb>

The followings are term lists for each information type entity.

- <Communication>: Tweet, DM, email, …
- <Disaster-threat>: Power is out, No power, People trapped, …
- <Multimedia>: photo, instagram, visualization, …

The seed terms we have defined are expanded using terms in thesaurus.com and relatedwords.org. We have assumed that each information type entity would give additional information for classification. For example, the entities such as <Government> and <Organization> would be helpful for the category 'Official', an entity <News> for the category 'ContinuingNews', an entity <Disaster/threat> for the category 'EmergingThreats', and an entity <Evacuation> for the category 'MovePeople'.

2.4 URL Entities

A URL itself has information as represented by the URL. We have defined URL entities such as <URLVideo>, <URLPhoto>, <URLNews>, <URLWeather>, <URLOrganization>, <URLDonation>, <URLDisaster> and <URLBlogMagazine>.

We have assumed that each URL entity would give information for a category. For example, the entity <URLDonation> would be helpful for the category 'Donations', an entity <URLWeather> for the category 'Weather', an entity <URLOrganization> for the category 'Official', an entity <URLNews> for the categories 'ContinuingNews' or 'PastNews', an entity <URLDisasterInfo> for the category 'EmergingThreats', and the entities <URLVideo> and <URLPhoto> for the category 'MultimediaShare'.

In order to extract useful URLs, the TREC-IS training data and CrisisT26 dataset are used. For pre-processing, a short URL is converted to an original URL. The URLs with more than frequency 10 have been defined as 8 entities. The followings are term lists for each URL entity.

- <URLPhoto>: instagram.com, twitpic.com, facebook.com/photo.php, …
- <URLOrganization>: usgs.gov, rfs.nsw.gov.au, redcross.org, …

2.5 User Entities

Based on a user's characteristics, we have defined user entities such as <UserNews>, <UserWeather>, <UserOrganization>, <UserDonation>, <UserDisasterInfo>, and <UserMultimedia>.

In order to extract useful user information in tweets, the TREC-IS training data and CrisisT26 dataset are used. The users with more than frequency 10 have been defined as 6 user entities as the characteristics. We have assumed that a user entity <UserDonation> would be helpful for the category 'Donations', a user entity <UserWeather> for the category 'Weather', an entity <UserNews> for the categories 'Factoid', 'ContinuingNews' or 'PastNews', an entity <UserOrganization> for the category 'Official', and an entity <UserMultimedia> for the category 'MultimediaShare'.

The followings are tweet user lists for each user entity.

- <UserWeather>: @dost_pagasa, @breakingstorm
- <UserDisasterInfo>: @NewEarthquake, @INGVterremoti

Table 1. Examples of Conceptual Representation

Conceptual Entities	Examples		# of Entities
Event Entity	<EventLoc>	#colorado, #costarica, #LAX, …	3
	<EventCri>	#Wildfire, airport shooting, #Typhoon Bopha, …	
Category Indicator Entity	<Movepeople>	evacuation, leave town, pre-evacuation notice, …	25
	<Weather>	#weather, forecast, satellite image, …	
Information Type Entity	<Unit>	magnitude, dollars, acres	21
	<Evacuation>	leave NOW, evacuation orders, closed the highway, …	
URL Entity	<URLNews>	yahoo.com/news, reuters.com, cbsnews.com, …	8
	<URLDonation>	worldvision.org.ph, prizeo.com, secure.redcross.ca	
User Entity	<UserNews>	@BreakingNews,@ChannelNewsAsia,@CBSNews, …	6
	<UserOrganization>	@LarimerSheriff, @HumaneSociety, @RedCross, …	

3. Deep Learning Models for Crisis-Related Tweet Classification

In this experiment, we have used combining deep learning models which combine class activation mapping with one-shot learning in convolutional neural networks. The class activation mapping is generated using global average pooling in Convolutional Neural Networks(CNNs). Then, one-shot learning is applied in CNNs. The expected effect using combining deep learning models is that crisis-related terms and conceptual entities would be emphasized for classification.

3.1 Generation of Class Activation Mapping for Text Classification

In image localization, class activation mapping highlights the class-specific discriminative regions [2]. Class activation mapping can identify the importance of the image regions most relevant to the particular category. We expect that the class activation map for text classification represent the importance of terms.

In this paper, class activation mapping is applied for text classification. The class activation mapping is generated by multiplying the weight from the convolution layer and the weight used for classification using the global average pooling in CNNs. As shown in Fig. 1. This allows us to check the importance of terms in the input data. Through learning, global average pooling creates class activation mapping and represents terms. The proposed method readjusts the terms weight in order of importance and re-inputs them.

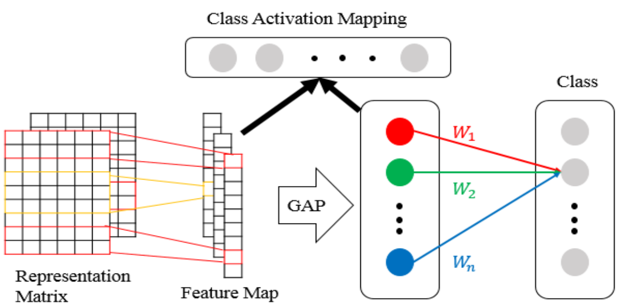

Fig. 1. Generation of class activation mapping for text classification

3.2 One-shot Learning in CNNs

There has been research using One-shot learning in LSTM (Long-Short Term Memory). It improves classification accuracy using One-shot learning. And it fixes the problem that the number of data is too small to learn [3,4]. We apply this method in CNNs and expect effectiveness.

CNNs consists of a convolutional layer, a maximum pooling layer, and a fully connected layer [5]. One-shot learning uses CNN's document vectors that come from fully connected layer and category vectors that represent each category. One-shot learning finds a category vector corresponding to the matched category, learns the index of similarity of the document vector and sets the value to 1. In the other case of finding, the category vector corresponding to the unmatched category, it sets the value of index of similarity to zero.

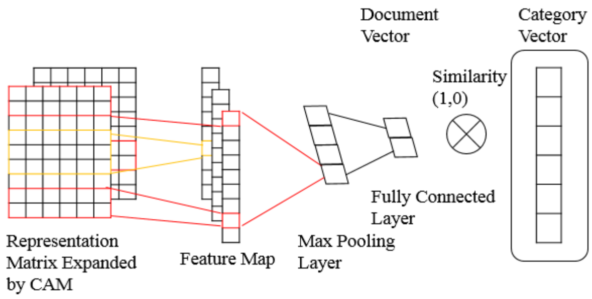

Fig. 2. One-shot learning in CNNs

3.3 Combining Class Activation Mapping with One-shot Learning in CNNs

The class activation mapping is used to represent terms with high importance of classification. We use a weighted readjustment of terms in order of importance and input them to CNNs model applying One-shot learning. The terms are continuously changed through the learning of the weights of the terms having high importance, and the readjusting of the terms is also performed.

4. SUBMITTED RUNS

We have compared conceptual representations for crisis-related tweets as follows:

- Conceptual Representation 1: Tweets are represented by terms, event entities, category indicator entities, and information type entities.
- Conceptual Representation 2: Tweets are represented by terms and all conceptual entities we have defined such as event entities, category indicator entities, information type entities, URL entities, and user entities.

We have compared classification methods for our conceptual representation as follows:

- Support vector machines (SVM): a set of supervised learning methods used for classification [6].
- Combining deep learning models: class activation mapping with one-shot learning in CNNs.

4.3 Run Description

The submitted runs are described as follows.

- cbnuS1: SVMs for Conceptual Representation 1
- cbnuS2: SVMs for Conceptual Representation 2
- cbnuC1: Combining deep learning models for Conceptual Representation 1
- cbnuC2: Combining deep learning models for Conceptual Representation 2

4.2 Experimental Results

The experimental results of information type categorization for multi-type and any-type are shown in Table 2 and Table 3, respectively. Table 4 shows experimental results per each information type performance for multi-type.

Table 2. Experimental results for Information Type Categorization (Multi-type)

Run ID	Precision	Recall	F_1	Accuracy
cbnuS1	0.219	**0.116**	0.125	0.905
cbnuS2	**0.267**	0.112	**0.126**	**0.906**
cbnuC1	0.239	0.102	0.115	0.901
cbnuC2	0.231	0.102	0.116	0.903
Median	0.183	0.078	0.082	0.899

Table 3. Experimental results for Information Type Categorization (Any-type)

Run ID	Precision	Recall	F_1	Accuracy
cbnuS1	0.447	0.740	0.558	0.406
cbnuS2	0.456	**0.778**	**0.575**	**0.421**
cbnuC1	0.506	0.480	0.492	0.354
cbnuC2	**0.532**	0.533	0.533	0.389
Median	0.398	0.616	0.477	0.338

Table 4. Information Type Categorization (Multi-type) per Information Type Performance

			Run ID											
			cbnuS1			cbnuS2			cbnuC1			cbnuC2		
Category		Support	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1
Request	GoodsServices	126	0	0	0	0	0	0	0	0	0	0	0	0
	SearchAndRescue	286	0	0	0	0	0	0	0	0	0	0	0	0
	InformationWanted	172	0.05	0.01	0.01	0.17	0.01	0.02	0.25	0.01	0.01	0	0	0
CallToAction	Volunteer	116	0	0	0	0	0	0	0	0	0	0	0	0
	Donations	804	0.38	0.58	0.46	0.48	0.47	0.47	0.64	0.43	0.52	0.62	0.46	0.53
	MovePeople	27	0.06	0.26	0.10	0.05	0.19	0.07	0.23	0.11	0.15	0.05	0.04	0.04
Report	FirstPartyObservation	3807	0.31	0.01	0.02	0.37	0.01	0.01	0.12	0	0	0.47	0	0
	ThirdPartyObservation	4160	0.25	0	0	0.30	0	0	0.5	0	0	0.25	0	0
	Weather	1325	0.51	0.17	0.25	0.53	0.17	0.25	0.6	0.11	0.18	0.62	0.15	0.24
	EmergingThreats	686	0.06	0.01	0.02	0.07	0.02	0.03	0.05	0	0	0.07	0.01	0.01
	SignificantEventChange	415	0.03	0.01	0.02	0.02	0.01	0.01	0.02	0	0	0.03	0	0.01
	MultimediaShare	3974	0.41	0.25	0.32	0.40	0.46	0.43	0.4	0.22	0.28	0.48	0.26	0.34
	ServiceAvailable	1076	0.39	0.09	0.15	0.37	0.09	0.15	0.61	0.03	0.07	0.57	0.03	0.06
	Factoid	2383	0.40	0.18	0.25	0.38	0.18	0.25	0.38	0.14	0.21	0.4	0.14	0.21
	Official	403	0.14	0.04	0.07	0.18	0.05	0.08	0.2	0.09	0.13	0.18	0.07	0.10
	CleanUp	62	0	0	0	0	0	0	0	0	0	0	0	0
	Hashtags	3363	0	0	0	1	0	0	0	0	0	0	0	0
Other	PastNews	1351	0.59	0.01	0.01	0.45	0	0.01	0	0	0	0	0	0
	ContinuingNews	4871	0.40	0.35	0.37	0.43	0.31	0.36	0.46	0.26	0.33	0.50	0.28	0.36
	Advice	1209	0.17	0.10	0.13	0.18	0.05	0.08	0.23	0.05	0.08	0.27	0.06	0.09
	Sentiment	6952	0.73	0.44	0.55	0.72	0.42	0.53	0.68	0.42	0.52	0.64	0.48	0.55
	Discussion	2060	0.25	0.04	0.07	0.23	0.04	0.07	0.21	0.03	0.06	0.20	0.02	0.04
	Irrelevant	2605	0.20	0.25	0.22	0.21	0.23	0.22	0.16	0.31	0.21	0.17	0.31	0.22
	Unknown	77	0	0	0	0	0	0	0.01	0.26	0.02	0.01	0.19	0.01
	KnownAlready	1101	0.13	0.10	0.12	0.13	0.10	0.11	0.24	0.08	0.12	0.26	0.07	0.11

5. Conclusion

In this paper, we have presented the conceptual representation for crisis-related tweet classification. Experimental results show that the conceptual representation (run cbnuS2) is effective for classification with SVMs and our combining deep learning models.

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