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DEVELOPMENT OF A CHATBOT FRAMEWORK FOR SHIP SAFETY EDUCATION –BASED ON ACTUAL COMMUNICATION DATA BETWEEN A PORT CONTROL CENTER AND SHIPS–

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Abstract. *The advent of the data age and advances in artificial intelligence technology have led to innovations in various business areas. In particular, many attempts have been made to reduce the frequency at which marine accidents occur – attempts that have yet to include a data-driven approach. Most marine accidents occur when a vessel is approaching a port and preparing for berthing. Although the cause of the accident has many factors, it often involves difficulties in communication between the ship navigator and the control center. In particular, communication in English results in difficulties for navigators who do not speak English as their first language. To address this, proper English conversation education for sailors is very important. In order to support the issue, this study presents data and a framework for the development of a chatbot for ship safety education.*
Keywords: Maritime education, Chatbot framework, Deep learning, LSTM

1. **Introduction.** Today, developments in information and communication technology (ICT) have resulted in many changes to the maritime industry. Notably, changes are taking place in areas such as the efficiency of marine transportation, intelligent ship movement, and marine e-navigation [1-5]. In Korea, there have been recent attempts to combine ICT with maritime safety to prevent large ship accidents.

Many maritime accidents occur when an anchor is in (or departs from) port. There are many reasons for such accidents – one of the most common being unreliable communication between the ship and the port control station. Errors in English communication may occur as ships are frequently operated by sailors from diverse nationalities and controllers may not be native English speakers either. In order to solve these problems in each country, systematic English communication training for declarations is being implemented. However, tools have not yet been developed for this purpose.

As data and artificial intelligence technologies evolve, various technologies – such as chatbot – are being used as learning tools in communication. Chatbot is a system that

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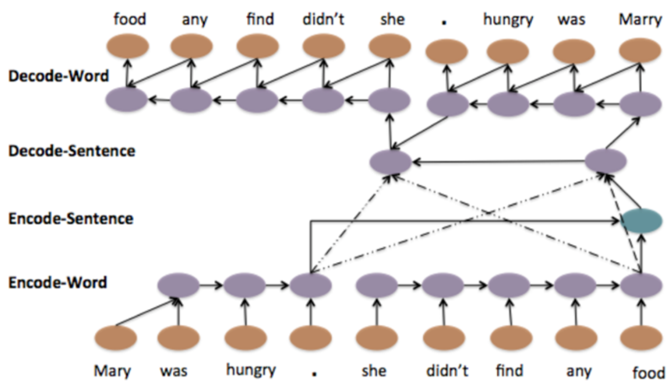
utilizes artificial intelligence technology to understand a user's query and respond accordingly [6]. Specifically, dialog data are gathered, both to understand the user's conversational attitude and to develop responses into a form that can provide the correct answer.

This paper aims to provide data and a framework for the development of a chatbot system that can be used for ship education in order to improve the efficiency of English communication between the vessel traffic service (VTS) and the vessel. Until now, there was no dialog data specific to the maritime environment, which made it difficult to develop a maritime educational chatbot. This paper proposes a framework for composing chatbots by collecting real chat data (between the VTS and the vessel) and utilizing a machine learning approach. Through this, we hope that it will be used as a seed in the future development of a maritime educational chatbot.

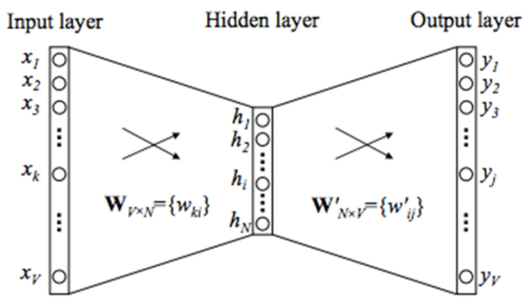
2. Groundwork.

2.1. Chatbot framework. Chatbot is emerging as the most actively applied business framework utilizing artificial intelligence technology. In particular, automated responses and an easy interface are the strengths of the system. In recent times, a variety of tools and algorithms for developing chatbots have been announced and the accuracy of development productivity and response has risen to the commercial level. In the field of education, chatbots are developed for use with infants, adults and specialty demographics [7,8].

2.2. Deep learning. Deep learning is a machine learning technology that involves building models with many neural layers to be used for pattern recognition and feature learning. This technology has grown rapidly since 2013. Word2Vec [9,10] and iterative neural network [5,8] are among the various techniques of in-depth learning. These methods involve receiving and processing the individual elements constituting sequential data, storing the processed information, and generating internal nodes corresponding to the input time. Speech recognition neural networks (such as the language recognition neural network) are suitable for sequential information processing (output according to need) and demonstrate excellent performance in string processing. Word2Vec technology is used to vectorize the word information used in chatbots. Word2Vec has been proposed to represent consecutive words in vector space and introduces the concept of similarity in existing natural language processing (NLP) technology to establish an easy learning method in large data sets.



(a) LSTM structure example



(b) Word2Vec structure

FIGURE 1. LSTM & Word2Vec structure

3. **Data.** To implement the chatbot system, we first needed to collect relevant conversation data. In this study, we collected the conversation data of the Ulsan VTS – the representative port of Korea – and used it to implement the chatbot system. We collected a total of 21,436 conversations between the VTS and ships at Ulsan port. The conversations were divided into 125 dialog cases and 13 action categories. The 13 action categories include navigation information, anchoring, docking, and departure. All data were collected and organized by humans.

The format of the collected data is as follows.

Port	Case	Category	Script Number	Port N.	ShipNumber N.		Script	Move	Step	Strategy	Date
Ulsan	1	PL	UL-PL-01-01.1		S1	EN	Ulsan vts Ulsan vts	Calling	Start	VTS Center	1:49:31 AM
Ulsan	1	PL	UL-PL-01-01.2		S1	EN	This is [SN]	Calling	Guide	Shipment name	
Ulsan	1	PL	UL-PL-01-01.3		S1	EN	HPWV	Calling	Guide	Call sign	
Ulsan	1	PL	UL-PL-01-01.4		S1	EN	Please come in	Calling	Request	Response	
Ulsan	1	PL	UL-PL-01-01.5		S1	EN	over	Calling	Turn Taking	Over	
Ulsan	1	PL	UL-PL-01-02.1	V1		EN	[SN]	Calling	Response	VTS Center	
Ulsan	1	PL	UL-PL-01-02.2	V1		EN	go ahead	Calling	Request	Start reporting	
Ulsan	1	PL	UL-PL-01-03.1		S2	EN	Good evening ma'am	Calling	Greetings	Evening	
Ulsan	1	PL	UL-PL-01-03.2		S2	EN	Just want to confirm what time pilot will be boarding on	Leading wire	Question	Boarding time	
Ulsan	1	PL	UL-PL-01-04	V2		EN	Please check channel 13	Leading wire	Guide	Channel	
Ulsan	1	PL	UL-PL-01-05.1		S3	EN	13 ok	Leading wire	Reception	Channel	
Ulsan	1	PL	UL-PL-01-05.2		S3	EN	I will be contact with pilot	Leading wire	Intent	Calling	1:49:54 AM
Ulsan	2	PL	UL-PL-02-01.1		S1	EN	Ulsan pilot, Ulsan pilot	Calling	Start	coast pilot	4:33:32 AM
Ulsan	2	PL	UL-PL-02-01.2		S1	EN	[SN]	Calling	Guide	Shipment name	
Ulsan	2	PL	UL-PL-02-02	V1		EN	[SN] vts	Calling	Answer	VTS Center	
Ulsan	2	PL	UL-PL-02-03.1		S2	EN	Yes good morning Ulsan vts	Calling	Greetings	Morning	
Ulsan	2	PL	UL-PL-02-03.2		S2	EN	This is [SN]	Calling	Guide	Shipment name	
Ulsan	2	PL	UL-PL-02-03.3		S2	EN	3FUX3	Calling	Guide	Call sign	
Ulsan	2	PL	UL-PL-02-04	V2		EN	[SN] What is your ETA?	Navigation information	Question	ETA	
Ulsan	2	PL	UL-PL-02-05.1		S3	EN	My ETA to pilot station is 06'30	Navigation information	Guide	ETA	
Ulsan	2	PL	UL-PL-02-05.2		S3	EN	over	Navigation information	Turn Taking	Over	
Ulsan	2	PL	UL-PL-02-06.1	V3		EN	06'30	Navigation information	Reception	ETA	
Ulsan	2	PL	UL-PL-02-06.2	V3		EN	Copy	Navigation information	Reception	Response	
Ulsan	2	PL	UL-PL-02-06.3	V3		EN	And last port?	Navigation information	Question	Prior port	
Ulsan	2	PL	UL-PL-02-07.1		S4	EN	My last port of call, Dakoma Washington, USA	Navigation information	Guide	Prior port	
Ulsan	2	PL	UL-PL-02-07.2		S4	EN	over	Navigation information	Turn Taking	Over	
Ulsan	2	PL	UL-PL-02-08.1	V4		EN	USA	Navigation information	Reception	Prior port	
Ulsan	2	PL	UL-PL-02-08.2	V4		EN	Copy	Navigation information	Reception	Response	

FIGURE 2. An example of conversation data

4. **A Chatbot Framework.** The recurrent neural networks (RNNs) take account of real-time input data and previously collected data.

The overall structure of our proposed chatbot framework is shown in Figure 3.

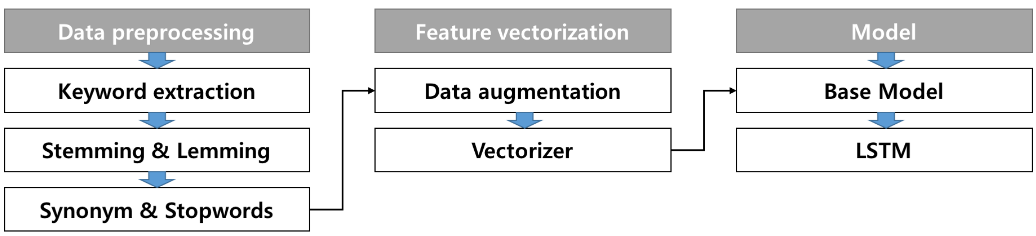


FIGURE 3. The overall structure of the proposed chatbot framework

It is first necessary to preprocess the given dialog data set. The reason for preprocessing is to extract a clear feature that can be used to classify the conversation. To accomplish this, we use natural language processing methodologies, such as keyword extraction and synonym processing. Subsequently, we apply data augmentation to improving the classification performance. Our goal is to build a model that performs better as the number of restricted keywords increases. Using the extracted features, we attempt to construct a classification model that will provide answers to the questions in the dialog.

4.1. **Data preprocessing.** Keyword extraction and similar processing methods are important for extracting the features of effective dialog data. In general, a sentence may consist of nouns, verbs, adverbs, conjunctions, and so on. In particular, words such as nouns, adjectives, and verbs are central to representing sentence features. It is of particular importance to extract these keywords through data preprocessing. Additionally, it is necessary to extract synonyms from the extracted keywords. In general, users of chatbot use various synonyms instead of always resorting to the same word. As such, it is necessary to add similar words in order to cope with them properly.

[SN] What is your ETA? → What, ETA	"final port, Ulsan" → "last port, Ulsan"
Keyword extraction example	Synonym example

In order to clarify the question/answer in this process, it is necessary to tag part of speech and to eradicate stopwords. We use NLTK – a natural language processing module in python – for this purpose.

4.2. **Feature vectorization.** To create a model that classifies conversation data, the data must be transformed into a vector that is understandable by the computer before it is input. As such, we first perform data augmentation in which synonyms are added with new syllabic keyword information. Subsequently, we use two techniques to convert the generated and augmented keyword vector into a processable feature vector. The first technique involves defining the "number of feature" dimension as 2000. This dimension is not the number of words, but rather is defined by the ord() function, which specifies the index of the word and then allocates the vector using the length of the word. The second technique involves changing the index value for each corresponding area using 1gram, 2gram; 1char, 2char, and so on. The examples of feature vectorization are as follows:

1gram → 2000vector[ord(My) % 100] = len(MY), . . .
2gram → 2000vector[ord(My last) % 100] = len(My last), . . .
1char → 2000vector[ord(M) % 100] = len(M), . . .
2char → 2000vector[ord(My) % 100] = len(MY), . . .

4.3. **Building a model.** We create the model using the generated feature vector. We use the long short-term memory (LSTM) of deep running – which has recently become very popular – along with traditional classification models, such as naive bayesian and random forest. LSTM supports classifying contiguous dialog data sets into models that are very robust to continuous conversation sets, such as chatbots.

5. **Conclusions.** This paper presents chatbot data for a learning and implementation framework to build a chatbot system for maritime safety education. Until now, communication data from a maritime environment had not been collected, making it difficult to implement a real chatbot. Our research has made the first contribution of contextual data for a maritime chatbot and proposed a practical framework for actual use. Based on the data collected in this study and the proposed LSTM framework, we have a plan to implement a practical chatbot system and apply it to the field for educational use. Further experiments are needed to improve the accuracy and sophistication of the proposed chatbot system.

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