Convolutional Neural Network and Bidirectional LSTM Based Taxonomy Classification Using External Dataset at SIGIR eCom Data Challenge

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ABSTRACT

In eCommerce websites, products are annotated with various metadata such as a category by human sellers. Automatic item categorization is useful to reduce this cost and have been well researched. This paper describes how we tackle SIGIR eCom DataChallenge 2018, whose goal is to predict each product's category by its title. We formulate the task as a simple classification problem of all leaf categories in a given dataset. The key features of our methods are combining of Convolutional Neural Network and Bidirectional LSTM and pretraining the proposed model with an external dataset (i.e. not given in this contest). An error analysis is also employed and some cases which are hard to predict accurately are revealed.

KEYWORDS

Convolutional Neural Network, Bidirectional LSTM, External dataset

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1 INTRODUCTION

In eCommerce websites, products are registered with metadata (e.g. title, category, etc.) by human sellers. Annotating products with those metadata is hard job, and therefore automatic predictions of metadata can reduce the cost[2]. In recent years, a number of studies of automatic item categorization in eCommerce have been made[1, 2, 9–11]. Pradipto *et al.*[1] reported that products are often categorized incorrectly because product taxnomies are large. Furethermore, if two different sellers annotate a same product with a title, the result should be different. Those difficulties cause a noisy dataset, and therefore automatic item categorization is difficult task.

At this challenge of SIGIR eCom DataChallenge 2018, Rakuten Institute of Technology provides train and test datasets. The train dataset is composed of product titles and category ID paths, and the test dataset contains only product titles. The goal of participants is to predict the category ID path for each product title in the test dataset. This challenge is more difficult than the previous item categorization problems for following two reasons: (1) The metadata of products is only title and any other information (e.g. price, image, etc.) is not concluded. (2) The dataset contains not category "name" paths, but category "ID" paths. This causes difficulty in using prior knowlede of each category.

This paper describes how we tackle SIGIR eCom DataChallenge 2018. We formulate the task as a simple classification problem of all leaf categories in the given dataset. The key features of our methods are following two parts: (1) Convolutional Neural Network and Bidirectional LSTM are used together. This technique may be useful because two models are different in structure. (2) Amazon Product Data, which contains product reviews and metadata from Amazon, is used to pretrain. In the area of natural language processing, it is reported that transfer learning is useful[7]. The trainig and test dataset given in this contest are very large, but many categories have only one product. Thus, pretraining with an external dataset may be useful for the given sparse dataset.

In the rest of the paper, the detail of our system is described in Section 2. Section 3 describes error analysis of our model. Finally, we present the conclusion in Section 4.

2 METHODS

An overview of our system is given in Figure1. A product title is fed to the system and a category for the product is predicted by following procedures: (1) The product title is split into words and they are normalized. (2) Each word is converted into an embedding vector. (3) The embedding vectors are input into "Multi-kernel CNN module" and "BiLSTM module". Each module outputs a flatten vector. (4) Two vectors from step (3) are concatenated into a flatten vector and passed into a last fully connected layer. Probabilities of all leaf categories are output from the fully connected layer.

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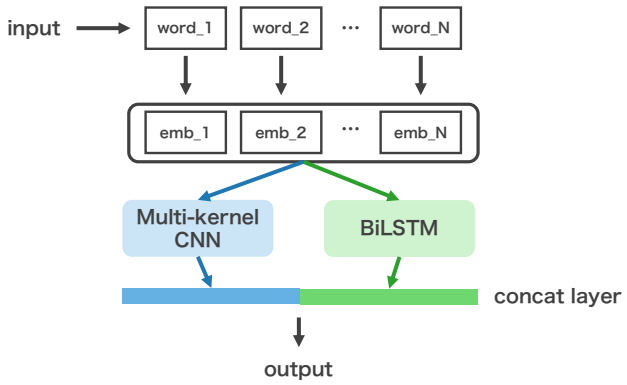

Figure 1: An overview of our system.

In the following of this section, we describe the detail of those procesures.

2.1 Preprocessing of a product title

First, the input sequence (i.e. product title) is split into some words by a space character. Then, symbol characters (e.g. %, #, etc.) in each word are removed. Finally, each of the words is converted into lowercase.

2.2 Generating embedding vectors

We used word2vec implemented by gensim[8] to generate skip-thoughts embedding vectors. The setting of word2vec is as follows.

- used all words appearing in train and test dataset
- window size is 7
- hierarchical softmax is used for model training
- negative sample size is 5
- embedding vector size is 512

2.3 Training Modules

We used Convolutional Neural Network with multiple kernels (Multi-kernel CNN)[4] and Bidirectional LSTM with Soft Attention[5] for training modules.

2.3.1 Multi-kernel CNN. Y. Kim[4] proposed a Convolutional Neural Network based method for sentence classification problem. We adopted the idea to predict categories and call this module "Multi-kernel CNN". An overview of "Multi-kernel CNN" module is given in Figure 2.

The input of this module is embedding vectors described in Section 2.2 and the output is a vector whose elements correspond to probabilities of each leaf category. First, the input is passed into one-dimensional convolutional layers and the outputs are feature maps. We used multiple convolutional layers different in kernel size (e.g. 2, 3, 4 and 5). Next, feature maps are flattened into a vector and it is passed into a last fully connected layer.

2.3.2 Bidirectional LSTM with Soft Attention. In recent years, Recurrent Neural Networks have been used in the area of natural language processing. In the field of neural machine translation, it is reported that attention mechanism is effective technique[5].

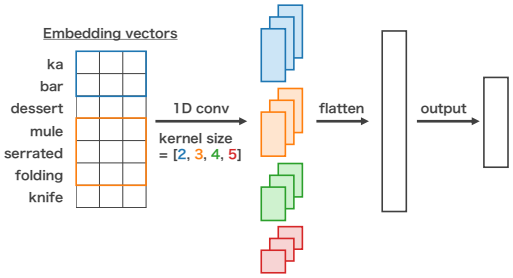

Figure 2: An overview Multi-kernel CNN module.

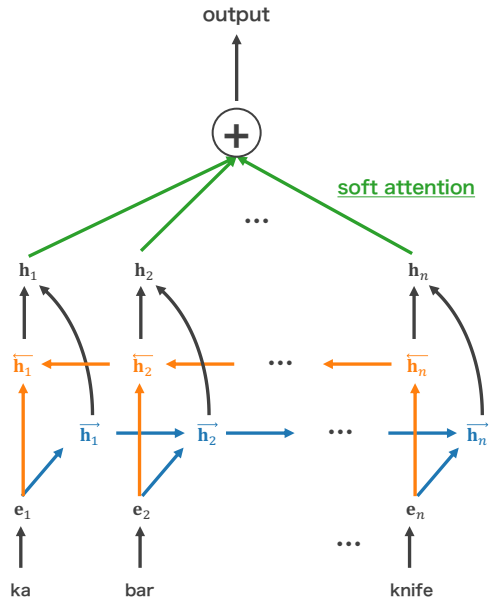

Figure 3: An overview of Bidirectional LSTM module.

We employed bidirectional LSTM with Soft Attention[5] to predict categories. We note that an attention layer of "sequence to sequence" model accepts what LSTM layers output from both of input-side and output-side sequences; however, this model is "sequence to label" and only output from input-side LSTM layers is accepted. An overview of "Bidirectional LSTM" module is given in Figure 3

The input and the output is same as "Multi-kernel CNN" module. First, the input is passed into a Bidirectional LSTM layer and the output is encoded sequence. Then, the encoded sequence is passed into a soft attention layer and the output is probability distribution over all leaf categories.

2.4 Concat two vectors from previous modules

"Multi-kernel CNN" module and "Bidirectional LSTM" module output two vectors whose elements correspond to probability distribution over all leaf categories. In this part, two vectors are concatenated into a flatten vector and it is passed into a fully concatenated

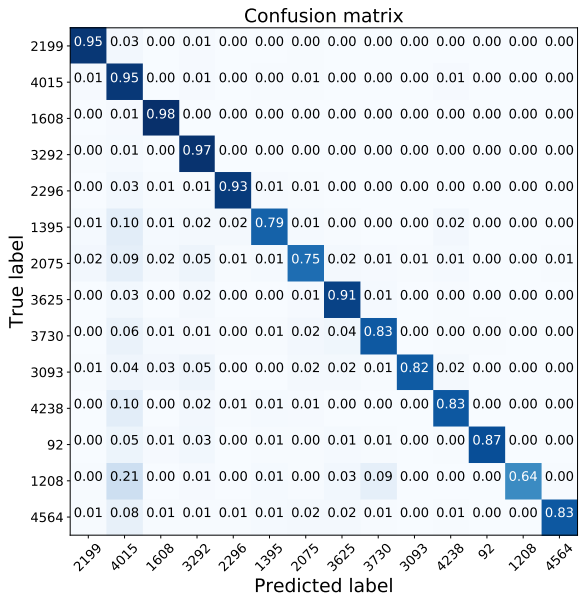

Figure 4: Confusion matrix of top level category prediction.

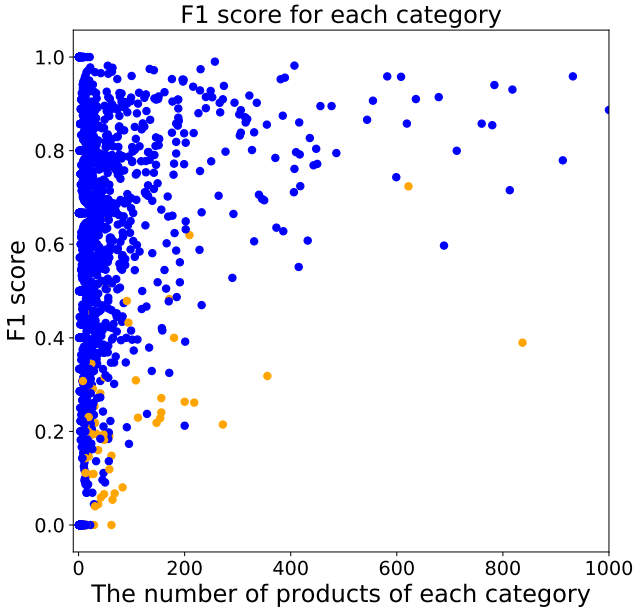

Figure 5: F1 scores for each category. The vertical line shows F1 score and the horizontal line shows the number of products in each category. The orange points show categories whose top level is "2296".

layer whose output is as same as the previous module (e.g. probabilities of each leaf category).

2.5 Pretraining

At this contest, participants are allowed to use an external dataset. We used Amazon Product Data[3, 6], which contains product revies and metadata from Amazon, to pretrain the model described before. The dataset contains a title and categories of each product and thus it can be used to pretrain our model. After pretraining with Amazon Product Data, our model is trained with the training dataset given in this contest.

3 ERROR ANALYSIS

We split the train dataset by this contest into two parts: train and validation part to check a performance of the proposed system.

3.1 Top level category prediction

First, we show the accuracy of top level category prediction. Figure 4 shows the confusion matrix of top level category prediction. It is found that products whose top level category is "1208" are often miss classified as "4015". In Table 1, examples which are miss classified "1208" as "4015" and products correspond to miss classified category are shown in Table 2. In the first and second lines in Table 1, true and predicted category are seem to be similar. More specifically, "1208>310>1629>1513>3369" and "4015>4454>473" seem to be a food category. "1208>546>4262>572" and "4015>3754>3580>1695" seem to be a DIY category. It is difficult to predict the categories of the products without a detail of the categories. For the miss classified case in the third line in Table 1, "Popcorn" is in the each title of products correspond to the predicted category "4015>2337>2943>2570>228". If products correspond to different categories have same words, it is hard to distinguish those categories.

3.2 Difficult Categories

In this sections, difficult categories are explored. Figure5 shows F1 scores for each category. It can be said that it is difficult to predict accurately for categories which few products are correspond to.

Furthermore, we focus on categories that are hard to predict in categories close to the number of products (i.e. bottom of the Figure5) and it is found that categories whose top level is "2296" are tend to bottom of the Figure5 (orange points). Table3 shows example products correspond to categories whose top level is "2296". It seems that the "2296" shows a media category, such as books and CD&DVD titles. It is found that the title of products in a media category tend not to have specific words to show its category. This causes difficulty in prediction for "2296" category.

4 CONCLUSION

In this paper, we describe how we tackle SIGIR eCom DataChallenge 2018. Our proposed model is combined Convolutional Neural Network and Bidirectional LSTM. We trained the model not only the given dataset but also the external dataset, Amazon Product Data. In error analysis, it is found that two categories which are similar or share same words in titles are hard to distinguish. It is also found that media categories are hard to distinguish because each title of

products in those does not have enough information. We believe that high prediction accuracy came from proposed deep learning models and the external dataset, but human prior knowlede for each category is useful to get better performance.

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Table 1: Examples which are miss classified top level category: "1208" as "4015"

title	true category	predicted category
Wabash Valley Farms 77809 Bring Home The Bacon	1208>310>1629>1513>3369	4015>4454>473
Cartoon Growth Height Measure Chart Wall Decor Sticker DIY Wallpaper Decal	1208>546>4262>572	4015>3754>3580>1695
Popcorn Micro Butter 3Pk -Pack of 6	1208>310>397>1635>587	4015>2337>2943>2570>228

Table 2: Example products correspond to miss classified categories.

category	title
4015>4454>473	Artichoke Ccktl Marinated -Pack of 12
	AzureGreen HACTCP 2oz Activated Charcoal Powder
	Muir Glen B04579 Muir Glen Crushed Tomato In Puree - 6x104 Oz
4015>3754>3580>1695	Unique BargainsButterfly Flower Print Removable Wall Sticker Decal DIY Wallpaper Decoration
	Unique Bargains Living Room Plum Blossom Pattern Adhesive Decal Wallpaper 60 x 45cm Wall Sticker
	Brewster Home Fashions DL30463 Accents Suelita Striped Texture
4015>2337>2943>2570>228	Cuisinart Air Popcorn Maker Cuisinart Popcorn Maker
	0.75 Ounce Movie Theater Popcorn Box (Pack of 50)
	Great Northern Paducah 8oz Popcorn Popper Machine w/Cart, 8 Ounce - Black

Table 3: Example products correspond to categories whose top level is "2296".

category	title
2296>2435>1576	Rawhide Down
	Scarlet Women
	The Quartet
2296>2435>3792	Alfred 00-21113 I Will Sing - Music Book
	Nocturnes and Polonaises
	Complete Preludes and Etudes-Tableaux
2296>3597>3064	Blues Heaven
	Dowin In The Delta
	Free Beer
2296>3597>3956	Regina Belle - Believe in Me
	New Edition
	Backyard - Skillet
2296>3706>1586	Suits-Season Three
	Newlyweds-Nick and Jessica Complete 2nd and 3rd Seasons
	Defiance-s3 [dvd] [3discs] (Universal)
2296>3706>3437	Log Horizon: Season 2 - Collection 2
	Yu Yu Hakusho Season 3
	Case Closed-Season 3-S.A.V.E.