Multimodal E-Commerce Product Classification Using Hierarchical Fusion

Tsegaye Misikir Tashu*, †, Sara Fattouh*, Péter Kiss* and Tomáš Horváth*†
*Department of Data Science and Engineering, Faculty of Informatics, ELTE - Eötvös Loránd University
Pázmány Péter sétány 1/C, 1117 Budapest, Hungary
†Faculty of Science, Institute of Computer Science, Pavol Jozef Šafárik University, Jesenáň 5, 040 01 Košice, Slovakia
‡College of Informatics, Kombolcha Institute of Technology, Wollo University, 208 Kombolcha, Ethiopia
Email: *misikir@inf.elte.hu, *sara.informatics@gmail.com, *peter.kiss@inf.elte.hu, *tomas.horvath@inf.elte.hu

Abstract—In this work, we present a multi-modal model for commercial product classification, that combines features extracted by multiple neural network models from textual (CamemBERT and FlauBERT) and visual data (SE-ResNeXt-50), using simple fusion techniques. The proposed method significantly outperformed the performance of the unimodal models, as well as the reported performance of similar models on our specific task. We made experiments with multiple fusing techniques, and found, that the best preforming technique to combine the individual embedding of the unimodal network is based on the combination of concatenation and averaging the feature vectors. Each modality complemented the shortcomings of the other modalities, demonstrating that increasing the number of modalities can be an effective method for improving the performance of multi-label and multimodal classification problems.

Index Terms—Transformers, pre-trained models, Ensemble, E-commerce, Multi-modal, Fusion.

I. INTRODUCTION

Product profiles on e-commerce platforms typically contain unstructured text, product titles, and images, and provide details about the product that is important to e-commerce. The profiles help customers make purchasing decisions and, on the other hand, provide input for automated services of e-commerce sites, such as question-answering and product recommendation systems. Since the number of products and the number of product categories in an e-commerce platform can be so high that it is unmanageable for humans, it is important to have methods that are able to accurately assign these products to their categories [3].

Most research on product classification has focused on the use of text-based cues, even though products on e-commerce platforms contain more than textual information and ignore the valuable information that associated images contain. Therefore, it might be useful to experiment with multimodal models that can combine features extracted from different modalities.

In this work, we proposed a multimodal product classification model based on several pre-trained transformer-based architectures for language modeling and image classification. The transformer-based language models were used to learn a representation of text features from the textual information, and pre-trained visual approaches are used to obtain a representation from images. We used hierarchical fusion to combine the representations obtained from the language models and the visual model, and a fully connected layer to perform the final classification.

We empirically evaluated the proposed method in the Multimodal Product Classification Task of the SIGIR 2020 E-Commerce Workshop Data Challenge. The results of the experiments show superior performance compared to unimodal and other multimodal methods. Our experiments have also shown that text-based classification models generally perform better than visual models. On the other hand, the inclusion of both modalities allows us to benefit from complimentary feature information and outperformed baseline approaches.

The remainder of the paper is organized into six sections. Section II describes related work relevant to our research. Section III presents our proposed multimodal hierarchical fusion model architecture, section IV presents the general experimental settings and implementation, while in section V we summarize the experimental results and discussion based on the experiments. Finally, section VI presents our conclusions.

II. RELATED WORK

In 2020, a large-scale competition to classify multimodal product data was organized as part of the SIGIR 2020 e-commerce workshop. The dataset was provided by Rakuten France, and each product included a title and a detailed description in French, as well as a product image. The task was to predict 27 category labels from four major genres: books, children, households, and entertainment. Several teams and researchers participated [2], [4], [9], [11]. The most common solution proposed by most authors was to fine-tune pre-trained text and image models as feature extractors and then use a bimodal fusion mechanism to combine predictions. Most teams used the Transformer-based model BERT [5] for text feature extraction and ResNet [6] for image feature

https://sigir-ecom.github.io/data-task.html
extraction. For bimodal fusion, the methods used were even more diverse. Roughly in order of increasing complexity, the methods included simple late decision-level fusion [9] and co-attention [2].

Bidirectional Encoder Representations from Transformers (BERT) is a state-of-the-art open-source language model [1]. BERT Models are fine-tuned for specific goals. Sun et al. [12] demonstrated improved text classification performance by using various strategies, such as layer selection, layer-wise learning rate, etc. BERT has been used in a variety of ways to improve language processing tasks. Variations of BERT, trained on large French corpora, include FlauBERT [8] and CamemBERT [10].

In this study, we will fine-tune the pre-trained French language models for each textual modality separately and the SE-ResNeXt-50 [7] for image products to extract features for each modality. The extracted features are hierarchically fused using different fusion strategies to make the prediction.

III. HIERARCHICAL FUSION MODEL

In this section, we describe our proposed model architecture for product type classification.

The core of our method is to project the unimodal representation sequences produced by the transformers $P$, $T_f$, $T_c$ and $D_f$, $D_c$ into a joint representation space, and then learn a classifier in this joint space:

$$y = f(Z(P, Z(T_f, D_f), Z(T_c, D_c)))$$

(1)

where $Z$ is a function that combines the extracted features, and $f$ is a neural network classifier that maps the features of the resulting joint space to a class prediction $y$. $P$ is the reduced image representation in SE-ResNeXt-50 [7], $T_f$, $T_c$, $D_f$, $D_c$ are the representation sequences extracted from the titles and the descriptions by FlauBERT [8] and CamemBERT [10] respectively.

The proposed hierarchical model uses state-of-the-art pre-trained architectures in the base models. When building the fusion model, we tried to keep it as simple as possible, since a simple architecture may show a close performance with sparing complexity and cost. The fusion architecture is a simple trainable module.

A. Text Encoding Models

We fine-tune the two French-language models, FlauBERT and CamemBERT, for encoding textual information of the product title and description into the textual sequence representation. FlauBERT [8] was trained with unsupervised masked language modeling (MLM, similar to BERT), while CamemBERT was pre-trained on French text based on Facebook’s RoBERTa model.

Given a textual product title sentence $T = (t_1, t_2, \ldots t_n)$, FlauBERT and CamemBERT give embedding sequences $T_f = (t_1 f, t_2 f, \ldots t_n f)$, and $T_c = (t_1 c, t_2 c, \ldots t_n c)$, while for a given textual product description $D = (d_1, d_2, \ldots, dm)$, FlauBERT and CamemBERT produce $D_f = (d_1 f, d_2 f, \ldots, d_m f)$ $D_c = (D c_1, D c_2, \ldots, D c_m)$ embedding sequences, respectively.

B. Image Encoding Model

The SE-ResNeXt-50 [7] model is used to obtain representations of product images. We replaced the last fully-connected (FC) layer of the pre-trained model and fine-tuned the model for our product categorization task (that will be removed for the feature extraction). Following the work of [13]–[15], an input image $I$ is re-sized to $224 \times 224$ and divided into $16 \times 16$ regions. Each region $I_i (i = 1, 2, \ldots, 256)$ is then sent through the SE-ResNeXt-50 model to obtain a regional feature representation, a.k.a. a raw image vector. The final image feature vector $P$ is then obtained by the average of all regional image vectors.

$$P = \frac{1}{N_r} \sum_{i=1}^{N_r} \text{ResNeXt}(I_i)$$

(2)

where ResNeXt$(I_i)$ is the raw image vector extracted via SE-ResNeXt-50 from region $i$, $N_r$ (256 in this work) is the number of regions. The final visual representation $P_{vis}$ is the average of all regional image vectors.

C. Multi-modal Joint Representation Learning

The visual features extracted by passing the input images through the SE-ResNeXt-50 model is represented by $P$. To fit the dimension of the representation obtained from the image to the textual representations, we used a 1D convolution layer with max pooling ($P \in \mathbb{R}^d$). Similarly, the textual features extracted by passing titles CamemBERT and FlauBERT models are represented as $T_c, T_f \in \mathbb{R}^d$ and descriptions.

through CamemBERT and FlauBERT models are represented as $D_f, D_c \in \mathbb{R}^d$. To combine the text and image features, we implemented the following fusing functions ($Z$):

- **Addition Fusion:** This operation is defined as the sum of input representations. Given two inputs representation $(x_1, x_2)$ of any modalities with the same dimension $d$, the addition operation results in an output $X_{add} = x_1 + x_2$, where $X_{add} \in \mathbb{R}^d$.

- **Concatenation Fusion:** This operation is defined as the representations’ concatenation across a dimension. In terms of the base models: $X_{con} = [x_1, x_2]$, where $X_{con} \in \mathbb{R}^{d \times 2}$ and $[\cdot, \cdot]$ is the concatenation operation.

- **Average Fusion:** this operation is defined as the mean of the input representations. $X_{avg}(x_1, x_2) = mean(x_1, x_2)$, where $X_{avg} \in \mathbb{R}^d$.

D. Architecture

The idea of our proposed method is training a fully connected neural network model, that takes its input from the hierarchically fused embedding vectors, that have been produced by the 3 unimodal networks, and generates a new probability vector over the target categories. Our investigations are aimed at finding the best ways to combine the representations found
by different individual models. The proposed architecture shown in Figure 1 consists of the following layers:

- The **input layer** receives and preprocess visual and textual modalities (Section ). We feed the textual base models individually with the product titles and descriptions, resulting in four different textual embeddings, and split the input images into regions then pass its individual regions to SE-ResReXt-50.

- The **representation layer** extracts the feature vectors from the preprocessed input data using the fine-tuned unimodal networks. It also combines the per region outputs of SE-ResReXt-50.

- In the **intermediate fusion layer**, embeddings of the text modalities (product title and description) learned from each language model (CamemBERT, FlauBERT) were first fused using one of our fusion method, then, the fused results from CamemBERT and FlauBERT were further fused to obtain the final vector representation for text modalities.

- In the **final fusion layer**, the image representations obtained by the fine-tuned SE-ResNeXt-50 are combined with the text embeddings obtained from the intermediate fusion layer.

- **Feed forward layer.** Finally, the fused vector is transferred to a three-layer fully connected neural network to obtain a classification result. The softmax activation function is used to generate the classifications.

When training the fusion model, the uni-modal network layers are frozen, the refined product description representations were combined to the refined product title representation to produce a single refined representation, which together with the reduced image representation serves as input to our fully connected neural network. The operations used in the fusion layers resulted in different variants of the proposed hierarchical architecture.

**IV. EXPERIMENTAL SETTINGS**

**A. Dataset**

To test the effectiveness of our proposed model, we used a dataset provided by Rakuten Institute of Technology for the Rakuten Multi-modal Product Data Classification and Retrieval Challenge. The data for this task contains 99K products, of which nearly 84K items were included in the training dataset. The text and image dataset contains 27 different product type codes and a total of 55K unique products. Children, Household, Entertainment, and Books are the four parent domains that group the entire product catalog. The text data is in French and consists of product title and description. The title field has a mean length of 11 words and a maximum of 56 words, while the description field has a mean length of 35 words and a maximum of 2068 words. The product images are all square with white or black borders and a resolution of 500 x 500 pixels. Each product has an image associated with it. We preprocessed the data and performed the following steps:

- Text Pre-processing: We tokenize the product title and description using the NLTK 2 tokenizer, lowercase the text and remove HTML tags.

- Product images: To fine tune the pretrained image models were augmented by randomly rotating, flipping, and extracting random crops from the original images.

- Product images were resized to a uniform size of 224 x 224 and normalized per channel using ImageNet mean and standard deviation.

**B. Implementation Details**

All our models were implemented in PyTorch. We used the FlauBERT_{base} architecture with encoded vocabulary, which has 138M parameters, and the CamemBERT_{base} architecture, which has 110M parameters. The FlauBERT and CamemBERT models were fine-tuned with a batch size of 32

[2]http://www.nltk.org
and a sequence length of 256 for 10 epochs. The SE-ResNeXt-50 model was also fine-tuned with a batch size of 32 for 20 epochs.

The learning module for the multimodal representation was fine-tuned with the pre-trained weights of the trained uni-modal base models. The uni-modal network layers were frozen, and we trained our proposed multimodal architecture using the feature fusion methods followed by the connected network with softmax output layer to perform the product classification. We used the categorical cross entropy minimization objective as the loss function, the AdamW optimizer with a learning rate value of $2 \times 10^{-5}$ for the text models and the Adam optimizer with $10^{-3}$ for the image model.

V. RESULTS AND DISCUSSION

The aim of multi-modal models was to combine the representations produced by the uni-modal models to get more accurate, confident and robust predictions. Multiple models have been produced, these models vary in terms of overall performance. We present our findings in the following sections. As the labels for the test set were not available, we split the original training set and used for training and testing purpose.

To evaluate the generalization power of our model, we used two different splits to train and evaluate our proposed methods. In the first phase, we used 90% for training and 10% for test. 10% from the training was also used as a validation set. In the second phase, we used 80% for training and 20% for test. 10% from the 80% training was also used as a validation set. The 90/10 split was used to obtain relatively the same size test set as in the challenge.

A. 90/10, Train/test Split

In the first experiment, we used a 90/10 split between training and testing, using 90% for training and 10% for testing the model. Table I shows the performance of each uni-modal model, namely CamemBERT-title, CamemBERT-description, FlauBERT-title, FlauBERT-description, and SE-ResNeXt-50 individually. Table II shows the multimodal hierarchical fusion models on the test set using the concatenation/average fusion method in the first fusion layer (fusion of text embeddings) and different combination methods in the last fusion layer.

| Model          | Accuracy | F1 Score |
|----------------|----------|----------|
| Concatenation Fusion | 92.86%    | 92.66%   |
| Addition Fusion  |  92.47%  | 92.26%   |
| Average Fusion   |  92.47%  | 92.26%   |

In the proposed hierarchical fusion architecture, it is noticeable that the model using the average combination in both fusion layers performs well.

B. Introducing More Layers

After running different experiments, the model using the average fusion method in both fusion layers showed the best performance compared to other models trained with a 90/10 split of the dataset. We started incrementally experimenting with Decision Layer by adding additional layers to further improve the performance of this model as follows:

- Adding a dropout layer after the last fusion layer.
- Stacking a dropout layer followed by a fully connected (FC) layer and a non-linearity before the final projection layer.

Table III presents the performance of the basic proposed architecture and the modified architecture having stacked dropout out, FC and non-linearity after the final fusion layer.

| Model          | Accuracy | F1 Score |
|----------------|----------|----------|
| Basic Model    | 93.20%   | 92.67%   |
| With Dropout   | 92.49%   | 90.00%   |
| With More Layers| 92.42%   | 91.11%   |

As we can see in Table III, the performance of the models decreased when we added more additional layers. Therefore, the modified model with more layers did not seem to improve the results, while the simplest architecture (Figure 1) showed better overall performance and reduced the training time, giving room for further experiments.
It is noticeable in the simplest hierarchical architecture that the model that used average combination in both fusion layers has a good performance on the test set. However, to obtain a robust model, further investigation is needed to verify that the model is not overfitted. To address the issue, we split the dataset in a way that allows us to obtain more test set, which is the second split strategy mentioned in section V.

C. 80/20, Train/Test Split

This split was performed to see how the models perform on less training set and a bit more test set. Table IV and table V shows the performance of uni-modal models and the proposed hierarchical model variations in terms of accuracy and F1 Score on the test set of the given dataset split, using Concatenation/Average fusion method in the first fusion layer (textual embeddings’ fusion) and different combination methods in the final fusion layer.

| Model                | Accuracy | F1 Score |
|----------------------|----------|----------|
| CamemBERT_description | 86.40%   | 83.13%   |
| CamemBERT_title      | 89.64%   | 84.01%   |
| FlaubERT_description | 85.81%   | 81.08%   |
| FlaubERT_title       | 88.98%   | 83.10%   |
| SE-ResNeX-50         | 57.20%   | 52.32%   |

We had the best performance when we used concatenation in the first and then averaging in the second fusion layer in the 80/20 split as shown in table V, but full average fusion outperformed the concatenation based models in the validation and test sets as evidenced in table II. The best model has achieved an overall F1 Score of 92.67%, which indicates that merging the two modalities boosts the performance compared to uni-modal networks.

VI. CONCLUSION

In this work, multiple Deep Learning based pre-trained and fine-tuned models were used with different fusion strategies with the goal of producing a simple, easily trainable and good quality model for multimodal e-commerce product classification. We used a dataset provided by Rakuten Institute of Technology for the Rakuten Multi-modal Product Data Classification and Retrieval Challenge that contains 27 different product type codes and a total of 55K unique products. The best performance was obtained using the average fusion operation in all fusion layers, where the model reached a F1-Score of 92.67% on the test set given 90/10 dataset split. When it came to 80/20 dataset split, the best achieved model was concatenation-based in fusing textual features, and average-based fusion in the final fusion layer with F1-Score of 92.46%. Our experimental results in general showed that fine-tuning pre-trained models for feature vector representation with simple hierarchical fusion approaches can yield good results in multimodal e-commerce product classification.

ACKNOWLEDGEMENTS

This research is supported by the ÚNKP-21-4 New National Excellence Program of the Ministry for Innovation and Technology from the source of the National Research, Development and Innovation Fund.

Supported by the Telekom Innovation Laboratories (T-Labs), the Research and Development unit of Deutsche Telekom.

Project no. ED_18-1-2019-0030 (Application domain specific, highly reliable IT solutions subprogramme) has been implemented with the support provided from the National Research, Development and Innovation Fund of Hungary, financed under the Thematic Excellence Programme funding scheme.

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