A Multimodal Late Fusion Model for E-Commerce Product Classification

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ABSTRACT

The cataloging of product listings is a fundamental problem for most e-commerce platforms. Despite promising results obtained by unimodal-based methods, it can be expected that their performance can be further boosted by the consideration of multimodal product information. In this study, we investigated a multimodal late fusion approach based on text and image modalities to categorize e-commerce products on Rakuten. Specifically, we developed modal specific state-of-the-art deep neural networks for each input modal, and then fused them at the decision level. Experimental results on Multimodal Product Classification Task of SIGIR 2020 E-Commerce Workshop Data Challenge demonstrate the superiority and effectiveness of our proposed method compared with unimodal and other multimodal methods. Our team named pa_curis won the 1st place with a macro-F1 of 0.9144 on the final leaderboard.

KEYWORDS

product categorization, multimodal, deep learning, e-commerce

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ACM Reference Format:
Ye Bi, Shuo Wang, and Zhongrui Fan. 2018. A Multimodal Late Fusion Model for E-Commerce Product Classification. In Proceedings of ACM Conference (Conference'17). ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

Product classification plays an important role in the e-commerce platform, with applications ranging from personalized search and recommendations to query understanding. Categorizing products precisely helps e-commerce websites provide customers with a better shopping experience [10]. Manual annotation approach is not feasible for large-scale industrial deployment, so there remains a need to develop automatic product categorization systems.

However, one should note that the construction of such systems is also a challenging problem. The number of product categories could be enormous and the distribution of product quantities across categories could be highly unbalanced. Moreover, there could be a large amount of noise in the textual and image data of products. Massive efforts have been made to deal with the important yet tough problem, which can be broadly divided into two categories including unimodal based approaches and multimodal based approaches. Particularly, the former either trains an image classifier based on product images or trains a text classifier based on textual information to categorize the product [1, 5, 11], whereas the latter attempts to build a classifier which combines product information from multiple modalities [3, 10, 12]. Most fusion techniques for multimodal learning can be grouped into feature-level fusion and decision-level fusion [12].

The goal of SIGIR 2020 E-Commerce Workshop Data Challenge is to solve a fairly large-scale multimodal (text and image) product classification problem. Given a training set of products with title, description and image information, and their corresponding product type codes, the participants need to predict the corresponding product type codes for an unseen held out test set of products. To tackle this challenge, we explored the feature-level and the decision-level fusion scheme to leverage multimodal product information. And the decision-level fusion scheme achieved better classification performance than the feature-level one under our experimental settings. For the decision-level fusion, the modal-specific classifiers are built from textual and image modal data respectively in the first stage. Then the late fusion strategy is learned from the class probabilities predicted by each modal classifier in the second stage.

The rest of the paper is organized as follows: Section 2 describes the challenge dataset. Our solution is introduced in Section 3 in details. We show the experiments and results in the next Section 4. Finally, we conclude our analysis of the challenge.

2 DATASET

In this section, we give a brief introduction of the challenge dataset. The organizer released approximately 99K product listings in tsv format, including 84,916 samples for training, 937 samples for phase 1 testing and 8435 samples for phase 2 testing. The dataset consists of product titles, descriptions, images and their corresponding product type codes. There are 27 product categories in the training dataset and the number of product samples in each category ranges from 764 to 10,209. The frequency distribution of categories in the training dataset is shown in Figure 1.

3 METHODOLOGY

In this section, we introduce our proposed methods for the multimodal product classification task. We first introduce the text and image based product classifier respectively and then we describe the fusion method in details. The ensemble strategy is presented
Figure 1: The frequency distribution of categories in the last. The overview of the proposed methods is shown in Figure 2. The source code will be released on github soon.

| Title                  | Description | Noise Reduction |
|------------------------|-------------|-----------------|
| CamemBERT              | ResNet      |                 |

Decision-level Fusion

3.1 Text classifier

The emergence of pretrained models (PTMs) has brought natural language processing (NLP) to a new era [9]. Recently, substantial work has shown that PTMs on the large corpus can learn universal language representations, which are beneficial for downstream NLP tasks and can avoid training a new model from scratch. For the text based product classifier, we leveraged the state-of-the-art French PTM CamemBERT [7] since most of the product titles and descriptions are written in French.

3.1.1 preprocessing. Preprocessing is the preliminary step for most NLP tasks and responsible for the final performance to some extent. We simply remove the excessive space and some HTML tags like `<l>` and `<p>` from product title and description texts.

3.1.2 text model. CamemBERT is a state-of-the-art language model for French based on the RoBERTa [6] architecture pretrained on a large amount of French corpus, and achieves improved performance in many downstream tasks for French over previous monolingual and multilingual approaches. We concatenated the preprocessed product title and description text with [SEP] token and sent them as text pair into the CamemBERT model. The pooled output of CamemBERT is taken as text representation, which is a 768 (CamemBERT-base) or 1024 (CamemBERT-large) dimensional vector. A fully connected layer is employed as a linear classifier.

3.2 Image classifier

Pretrained models are not just available for NLP tasks but also computer vision applications. For the image based product classifier, we employed the commonly used ResNet152 network [4] pretrained on the ImageNet dataset. The image classifier is trained using destruction and construction learning (DCL) [2], a fine-grained image recognition framework. Moreover, we applied the noise reduce techniques on the image dataset before training the image classifier.

3.2.1 noise reduction. By looking at the pictures of each type of product in the training set, we found that there may be some label errors. For example, the images shown in the Figure 3 are sampled from Prdtypecode 1180. Although we don’t know exactly what types of product the code 1180 refers to, it’s clear that the image on the left should not fall into that category. In other words, the left image could be noise.

If the classifier is trained with these noisy images directly, its performance could be degraded. In view of this, we attempted to find label errors in the image dataset with an open source tool cleanlab [4], a framework powered by the theory of confident learning [8]. Specifically, we trained multiple ResNet50 image classifiers to compute the predicted product category probabilities for all the training samples in a cross-validation manner. Then the cleanlab tool could utilize the matrix of predicted probabilities to find noisy samples, ordered by likelihood of being an error. We removed the top 10% noisy samples from the training set.

3.2.2 image model. Although there are 27 product type codes in the training set, they belong to only 4 top level categories (Child, Books, Household and Entertainment). This implies that the differences of images among different product subcategories within the same top level category could be small. So we treated the image based product classifier as a fine-grained image recognition task. The DCL method has shown its effectiveness on the fine-grained product recognition task and won first place in multiple product recognition challenges. Following the DCL scheme, we first...
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3.3 Fusion method
To tackle the multimodal product classification task, we mainly
tried two types of multimodal fusion methods which can be broadly
divided into two categories [12]: feature level fusion and decision
level fusion. Regardless of the fusion strategy, we use the ResNet
and CamemBERT network to extract features of the image and text,
respectively.

3.3.1 feature-level fusion. Feature-level fusion method leverages
multimodal information by concatenating the features extracted
from specific unimodal network as the multimodal representation
vector, followed by an additional classifier. We tried different uni-
fication approaches such as concatenation, summation and even
by means of attention mechanism. We also experimented with dif-
ferent training strategies such as end-to-end and step-by-step [12].
Despite all of these experiments, the best results that we achieved
for feature-level fusion were inferior to those of the text unimodal
classifier. This leads us to turn to the decision-level fusion scheme.

3.3.2 decision-level fusion. In this approach, an input-specific clas-
sifier is learned for each modality and then a fusion strategy is
learned from the class probabilities predicted by each modal clas-
sifier. Decision-level fusion has shown better performance than
feature-level fusion in the product categorization task according to
the study by Zahavy et al [12]. We employed this fusion scheme
and trained the multimodal product classifier in a two-stage ap-
proach. To be specific, in the first stage, we trained the text and
image classifier described in 3.1 and 3.2, respectively. In the second
stage, we designed a shallow neural network classifier that took all
the class probabilities from the text and image classifier as input,
and output the 27-class probabilities.

3.4 Ensemble strategy
In the model ensemble stage, simple majority voting is used to
ensemble the multiple classifiers. Concretely, we ensembled 12
classifiers with the decision-level fusion approach, which were
generated from different model configurations as follows:

- different configurations for the text classifier, such as differ-
  ent backbone networks (CamemBERT-base and CamemBERT-
large), learning rates and batch size.
- different configurations for the image classifier. For example,
  whether to use the clean dataset after denoising and whether
to use the DCL training method could produce different can-
didate models. Moreover, models saved at the late training
  phase were also exploited.
- different configurations for the decision-level fusion. We
  tried 1-layer and 2-layer neural network classifiers.

| Table 1: The online Macro-F1 results(%) |
|----------------------------------------|
| Method       | Phase 1 | Phase 2 |
| Uni-Image Classifier | 69.21   | -       |
| Uni-Text Classifier  | 89.93   | -       |
| Feature-level Fusion | 89.87   |          |
| Decision-level Fusion | 90.94   | 90.17   |
| Ensemble     | -       | 91.44   |

4 EXPERIMENT
In this Section, we provide experimental settings and results.

4.1 Experimental Settings
We divided the full 84916 labeled samples randomly into training
and validation set at a ratio of 9:1. For the noise reduction part,
we performed 4-fold cross-validation to compute the matrix of
predicted probabilities. There are about 2120 training samples in
the top 10% noisy samples given by the cleanlab. The text classifier
is trained with AdamW optimizer and the initial learning rate is
3e-5 or 5e-5 and decreases linearly after a warmup period. The
batch size is set to 64 or 128 and the number of epochs is set 40.
The image classifier is trained with SGD optimizer and the initial
learning rate is 0.01 and decreases every 12 epochs at a rate of 0.1.
The backbone network is trained for 60 epochs in the first stage
and then fine-tuned with the DCL method for 20 epochs in the
second stage. We adopted the code 5 released by the author. For the
decision-level fusion scheme, we trained the decision-level fusion
policy on the validation set in a 8-fold cross-validation manner. The
hidden size in the 2-layer fusion neural network classifier is set
to 6. The fusion policy neural networks were trained with Adam
optimizer and the learning rate is set to 0.01. We trained the policy
network for 40 epochs and kept the checkpoint that has the highest
macro-f1 score on the validation set. The predicted results of 8
trained policy networks are assembled by majority voting when
inferencing on the test set.

4.2 Results
Here we compared the performance of our method with different
settings. The results on the test set are shown in Table 1. The online
results for some methods are not given due to the limit on the num-
er of times the results could be submitted online. From the results,
we can see that the decision-level fusion scheme achieves better
results than unimodal method and feature-level fusion method. And
the ensemble strategy also brings about performance improvement
on the online results.

5 CONCLUSION
In this paper, we introduced our solutions for the multimodal prod-
uct classification task in details on the SIGIR 2020 E-Commerce
Workshop Data Challenge. Extensive experiments were conducted
on the challenge dataset and the results proved the effectiveness
of our method. In the future work, we will perform some more

5https://github.com/JDAI-CV/DCL
experiments and get the results of some methods on the full test set as soon as the full test set is released with ground truth labels.

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