Multi-Label Product Categorization Using Multi-Modal Fusion Models

Pasawee Wirojwatanakul[1] **and Artit Wangperawong**[2]
[1]New York University, pw1103@nyu.edu
[2]U.S. Bank, artit.wangperawong@usbank.com

Abstract

In this study, we investigated multi-modal approaches using images, descriptions, and titles to categorize e-commerce products on Amazon. Specifically, we examined late fusion models, where the modalities are fused at the decision level. Products were each assigned multiple labels, and the hierarchy in the labels were flattened and filtered. For our individual baseline models, we modified a CNN architecture to classify the description and title, and then modified Keras' ResNet-50 to classify the images, achieving F_1 scores of 77.0%, 82.7%, and 61.0%, respectively. In comparison, our tri-modal late fusion model can classify products more effectively than single modal models can, improving the F_1 score to 88.2%. 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 classification problems.

Introduction

Background

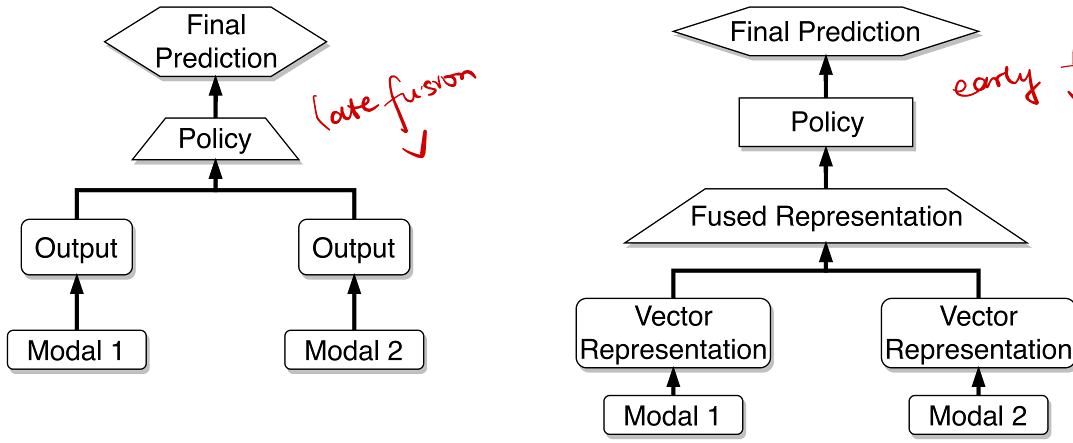
To sell products on many e-commerce systems, sellers are tasked with providing categories for their products. Automating product classification can reduce manual labor time and cost, giving sellers a better experience when uploading new products. Such auto-labeling can also benefit the buyers, as sellers manually tagging their own products may be inaccurate or sub-optimal. An performant classifier is important, as mislabelled products may lead to missed sales opportunities due to buyers not being able to effectively locate the things they want to buy.

Prior studies have approached product categorization as a text-classification task (Kozareva 2015; Yu et al. 2012; Vandic, Frasincar, and Kaymak 2018). However, ideally multiple types of inputs can be considered, including title, description, image, audio, video, item-to-item relationships, and other metadata. Although a few recent studies have explored product categorization using both text and images (Åberg 2018; Zahavy et al. 2016), here we report on a strategy for combining an arbitrary number of inputs and modes. We specifically demonstrate a multi-modal model based on images, titles, and descriptions. Our task is different from a regular multi-class classification problem, as a product may be labeled with more than one class. Most products will appear in many classes and sub-classes. Classes can be nested in another class and potentially nested in another sub-class. Given the large amount of products uploaded and the numerous possible labels applicable, machine learning can be used to automatically classify the products in a more efficient manner.

As images, titles and descriptions are different modalities of data that can each capture unique aspects of a product, we explored fusing individual models trained for each modality. Note that although fusing and ensembling both involve combining multiple models, for the purposes of our discussion each of the models utilize different modalities of data in fusion, whereas the same data passes through all of the models in an ensemble. There are two common ways to fuse different modal networks: late fusion and early fusion (Fig. 1). Late fusion refers to combining the predictions (outcome probabilities) of multiple networks using a certain policy. Such a policy can be using the maximum or minimum of the outcomes. In contrast, in early fusion vector representations of each modality can be extracted at an early level and fused with one another through concatenation or addition to produce a multi-modal representation vector. The model then performs classification on the resulting multi-modal representation vector.

Related Works

Convolutional neural network (CNN) architectures (Kim 2014) have been used to classify the title of products (Zahavy et al. 2016). In such a model, the first layer uses a random word embedding. The same study also used a VGG network for image classification (Simonyan and Zisserman 2014). While they experimented with both early and late fusion, only the late fusion resulted in an improvement in performance. The image and text classifiers were trained separately to achieve maximal performance individually before being combined by a policy network. The policy network which achieved the highest performance was a neural network with 2 fully-connected layers and took in the top-3 class probabilities from the image and text CNNs as input. Their dataset contained 1.2 million images and 2,890 possible shelves. On average, each product falls in 3 shelves.



late fusion

early fusion

Figure 1: The diagram on the left represents late fusion and the diagram on the right represents early fusion.

Their model is considered effective when the network correctly outputs one of the three shelves.

Existing studies have also used the image, title, and description of an ad/product to classify products into single categories (Åberg 2018). Åberg concatenated the title and description, and used fastText (Joulin et al. 2016) as the baseline model for text classification, while using the Inception V3 for image classification. Åberg also explored a similar implementation of Kim's CNN architecture (Kim 2014) but could not achieve the level of performance of fastText.

The Åberg study used a dataset containing 96,806 products belonging to 193 different classes. Since each product was assigned exclusively to one class, multi-label categorization was not addressed. Hence a softmax function could be applied in the final layer before outputting the class probabilities. Similar to work of Zahavy et al. described above, both late and early fusion were explored, and late fusion yielded better results. Both heuristic policies and network policies were explored. Heuristic policies refer to some static rule; as an example, the mean of the probabilities from different modals. Network policies refer to training a neural network that takes the output probabilities from different networks and produces a new probability vector.

Dataset

The dataset used in our study comprises of 9.4 million Amazon products (McAuley et al. 2015). The class hierarchical information was not available, as the classes and subclasses were pre-flattened as given. We randomly sampled 119,073 products from this dataset, in which the first 90,000 products are kept for the training set. After pre-processing, there are 122 possible classes in which a product can belong to. Unlike many previous studies, here each product can be assigned multiple labels. Each product in the dataset contains the image, description, title, price, and co-purchasing network.

Product categorization systems can be challenging to build due to the trade-off between the number of classes and efficacy. As an example, adding more classes and subclasses to a product might make it easier to discover, but more classes would also increase the likelihood of an incorrect class being applied. To address this issue, some studies reduced the number of sub-classes (Zahavy et al. 2016; Lyu, Lee, and Li 2017). One method is to create a shelf and categorize the products based on the shelves they are in. A shelf is a group of products presented together on the same e-commerce webpage, which usually contains products under the same categories (Zahavy et al. 2016). Since our dataset does not contain the webpage information necessary to form shelves, our method was to remove the classes containing less than 400 products.

On average, each product belongs to 3 categories after pre-processing. The maximum number of products in a category is 37,102 and the minimum number of products in a category is 558. On average, there are 2,919 products per category. In addition, we can see from Fig. 2 that the number of products per categories is not evenly distributed, which could introduce bias into the model.

Baseline Models

In order to understand how much we benefit from fusing the different modal classifiers, we report the baseline results for each modal below. We evaluate our results using the F_1 score (micro-averaged), which is an accepted metric for multi-label classification and imbalanced datasets (Yang and Liu 1999). During training, for all classifiers, we used Adam (Kingma and Ba 2014) as our optimizer and categorical cross-entropy as our loss function. To accommodate multi-labeling, the final activations for each classifier utilizes the sigmoid function. Although both titles and descriptions are textual data, we leverage their different use-cases by treating them as different modalities, allowing us to perform different pre-processing steps as described below.

Description Classifier

text

The description was pre-processed to remove stop words, excessive whitespace, digits, punctuations, and words longer than 30 characters. In addition, sentences were truncated to 300 words. To classify the pre-processed descriptions,

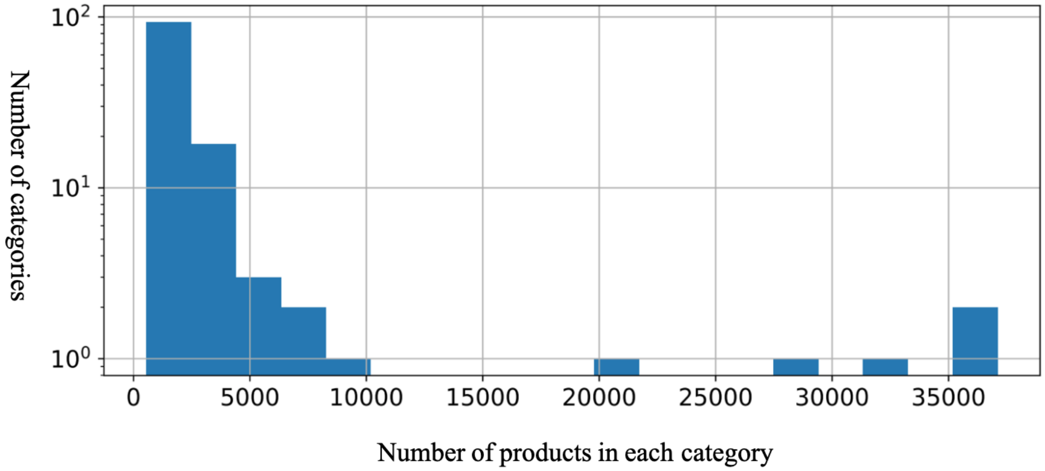


Figure 2: The x-axis represents the number of products in a category, whereas the y-axis represents the number of categories with that number of products.

we slightly modified Kim's CNN architecture for sentence classification. Kim's architecture is a CNN with one layer of convolution on top of word vectors initialized using Word2Vec (Kim 2014; Mikolov et al. 2013). Max-pooling over time is then applied (Collobert et al. 2011), which serves to capture the most important features. Finally, dropout is employed in the penultimate layer.

Unlike the models used in prior studies mentioned above (Kim 2014), we used GloVe as our embedding. Words not covered by GloVe were initialized randomly. For our dataset, GloVe covers only 61.0% of the vocabulary from the description. Our first convolution layer uses a kernel of size 5 with 200 filters. We then performed global max pooling, followed by a fully connected layer of 170 units with ReLU activations. Our final layer is another densely connected layer of 122 units with sigmoid activation. This model achieves 77.0% on the test set.

Title Classifier

Although an identical classifier to the description classifier was used for the title, the title data was pre-processed differently. For the title, we did not remove the stop words and limited or padded the text to 57 words. We again chose GloVe for the embedding, in which words not covered were initialized randomly. GloVe covers 77.0% of the vocabulary from the title. This model achieves 82.7% on the test set.

Image Classifier

We modified the ResNet-50 architecture (He et al. 2015) from Keras by removing the final densely connected layer and adding a densely connected layer with 122 units to match the number of labels we have. In addition, we changed the final activation to be sigmoidal. ResNet-50 is based on the architecture that achieves competitive results compared to other state-of-the-art models for image classification. We also used the pre-trained imagenet weights, which has been trained on the imagenet dataset (Deng et al. 2009), containing more than 14 million images. We kept the weights of the earlier layers frozen and trained only the deeper/later layers (Yosinski et al. 2014). We experimented with the number of trainable layers, in which our top model was trained on the last 40 layers, achieving a F_1 score 61% on the test set.

Summary

The results summarized in Table 1 underscore that the classifiers differ in discriminative powers as the title and description classifiers significantly outperform the image classifier. This result is consistent with previous similar studies reporting a significant difference between the image and title classifiers (Zahavy et al. 2016). Moreover, we have shown that the description classifier also significantly outperforms the image classifier. Such results suggests that text can provide more relevant information regarding a product's categories.

Table 1: F_1 scores for each individual classifier.

Modal	$\mathbf{F_1}$ **(%)**
Image	61.0
Title	82.7
Description	77.0

Error Analysis

Table 2 exhibits that the top misclassified categories for each classifier generally reflect their inadequate representation in the dataset. Recall that the average number of products per category is 2,919. The Accessories category contains the most products (924) out of all the misclassified categories, but it is still far below the average. In addition, we can see that the top misclassified categories for each classifier seldom overlap between the modal classifiers. For the categories that the image classifier performed poorly, the description and title classifiers perform better and vice versa.

Table 2: The top 15 most misclassified categories/classes for each classifier. The fraction represents the number of products which should be predicted as class c_i, but is not, over the total number of products that is in c_i.

Image	**Description**	**Title**
Martial Arts (146/154)	Women (107/134)	Horses (167/265)
Ballpoint Pens (192/203)	Accessories (663/924)	Novelty, Costumes & More (176/303)
Reptiles & Amphibians (136/144)	Clothing, Shoes & Jewelry (481/686)	Women (77/134)
Small Animals (327/349)	Boating (222/327)	Accessories (521/924)
Chew Toys (123/132)	Novelty, Costumes & More (194/303)	Feeding (137/244)
Squeak Toys (202/223)	Parts & Components (135/212)	Clothing, Shoes & Jewelry (384/686)
Cards & Card Stock (222/246)	Men (183/291)	Hunting & Tactical Knives (94/175)
Filter Accessories (108/120)	Chew Toys (83/132)	Balls (99/185)
Other Sports (188/210)	Balls (116/185)	Hunting Knives (80/152)
Bedding (154/174)	Boating & Water Sports (368/591)	Boating (171/327)
Tape, Adhesives & Fasteners (231/262)	Tape, Adhesives & Fasteners (161/262)	Small Animals (176/349)
Birds (432/490)	Office Furniture & Lighting (340/556)	Men (146/291)
Pumps & Filters (270/308)	Forms, Recordkeeping & Money Handling (196/323)	Chew Toys (65/132)
Cages & Accessories (125/144)	Hunting Knives (89/152)	Boating & Water Sports (275/591)
Horses (229/265)	Team Sports (228/399)	Carriers & Travel Products (65/142)

This suggests that we should be able to combine the classifiers to effectively complement each other's shortcomings for a more effective overall result.

Multi-Modality

As prior studies found that late fusion models were more effective than early fusion models (Åberg 2018; Zahavy et al. 2016), here we focus our studies on improving late fusion.

Predefined Policies

First we evaluated the efficacy of our models using predefined rules in order to compare with other non-static policies. We experimented with max policy and mean policy of the output from each of the classifiers. The max policy selects the highest output for each class prediction from among the image, label, and title classifiers. This can be represented as

$$o_{\max} = \max(o_{\text{image}}, o_{\text{title}}, o_{\text{description}}), \tag{1}$$

where $o_{\text{image}}, o_{\text{title}}, o_{\text{description}} \in R^{122}$ represent the output from each classifier, and the mean policy can be represented as

$$o_{\text{mean}} = \frac{o_{\text{image}} + o_{\text{title}} + o_{\text{description}}}{3}. \tag{2}$$

Both mean and max policy resulted in lower F_1 scores when compared to the top classifier, which is the title classifier. The mean policy yielded 81.7%, while the max yielded 78.8% F_1 scores. Intuitively, each classifier contributes equally to the mean policy. Therefore, we would expect that the average performance is less than that of the best performer. For the max policy, the erroneous maximal outputs from the low performing classifiers detriment the ultimate predictions.

Linear Regression

We trained a simple ridge linear regression model to fuse the individual classifiers into a single classifier. The model achieves 83.0% on the test set. The model can be considered

classifier1 classifier2 ... classifiern

linear regression

fusion classifier.

as minimizing the mean-squared error loss function according to

$$\min_{\boldsymbol{w}} ||\boldsymbol{w}\boldsymbol{X} - \boldsymbol{y}||_2^2 + \alpha||\boldsymbol{w}||_2^2, \tag{3}$$

where $\boldsymbol{y}$ is the true label, $\boldsymbol{wX}$ is the predicted label, and α is the L_2 regularization strength. Nevertheless, the simple non-static policy can outperform static policies above.

Bi-Modal Fusion

Prior studies involved two neural networks, one for classifying images and another for classifying titles, using late fusion (Zahavy et al. 2016). For comparison purposes, we examined models developed from fusing two of the three modal networks in this study. The first fused network includes the image classifier's output and the title classifier's output in a similar fashion with prior studies (Zahavy et al. 2016). We then fused the title classifier's output and description classifier's output for the second fused network and fused the image classifier's output and description classifier's output for the third network. All three networks were fused the same way, using a three layer neural network to concatenate the outputs from each of the classifiers. The first, second, and third layers contained 200, 150 and 122 units, respectively. All the activations were sigmoidal. The image-description, image-title, and description-title fused networks yielded F_1 scores of 82.0%, 85.0%, and 87.0%, respectively (see Table 3).

title description

image

end

Tri-Modal Fusion

Finally, we developed a tri-modal model to include the titles, images, and descriptions (see Fig. 3). To our knowledge, we are the first to fuse three classifiers/neural networks to categorize products. We fused the three classifiers as in the baseline models using a policy network, which is an additional neural network that takes in the output of each of the classifiers. We varied the number of layers, activation functions, and units of the neural networks. Through hyperparameter optimization, we found that the top policy network consists of three layers. It uses the sigmoidal activation on the first

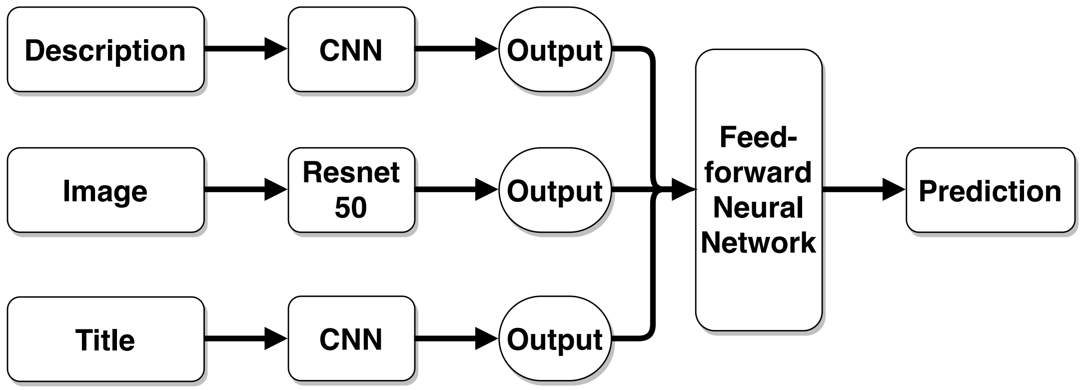


Figure 3: The proposed tri-modal fusion model architecture for product categorization using title, description and image.

and last layers and hyperbolic tangent activation on the middle layer. This fused model achieves an F_1 score of 88.2% surpassing all of the previous methods.

Table 3: F_1 scores for fused classifiers.

Model	$\mathbf{F_1}$ **(%)**
Max	78.8
Mean	81.7
Linear Regression	83.0
Image-Description Fused	82.0
Image-Title Fused	85.0
Title-Description Fused	87.0
Image-Description-Title Fused	88.2

Discussion

Compared to Table 2, the proportion of misclassified products has reduced significantly in Table 4. In examining Accessories, Horses, Clothing, and Shoes & Jewelry, we can see that the proposed method outperforms the individual classifiers by a considerable margin. However, the proposed method fails to significantly reduce the number of misclassified products on certain categories, such as Chew Toys. According to Table 2, each of the individual classifiers performed poorly predicting products as Chew Toys. This suggests that there remains categories that are underserved across all classifiers. To address this shortcoming, more data or other modes could be considered in future work. On the other hand, the result also suggests that as long as one classifier performs well on some of the tasks, it is sufficient for the overall model. For example, the number of misclassified products in Clothing, Shoes & Jewelry dropped from 384 to 256. Overall, this method improves over the top individual classifier and the top two-modals fused network by 5.5% and 1.2%, respectively (see Table 3).

Table 4: The top 15 most misclassified categories using our tri-modal fusion method.

	Fused Image-Title-Description
1	Chew Toys (64/132)
2	Accessories (417/924)
3	Women (58/134)
4	Novelty, Costumes & More (127/303)
5	Snacks (143/363)
6	Hunting Knives (59/152)
7	Men (112/291)
8	Clothing, Shoes & Jewelry (256/686)
9	Hunting & Tactical Knives (65/175)
10	Shampoos (58/158)
11	Balls (67/185)
12	Squeak Toys (79/223)
13	Horses (92/265)
14	Boating (113/327)
15	Airsoft (68/200)

Conclusion

We have shown that the title classifier can outperform the description classifier, and that the description classifier can outperform the image classifier. Moreover, a tri-modal fused network comprising of all three modalities outperformed any of the bi-modal fused networks. The performance improvements can be attributed to each of the classifiers addressing at least complementary portions of the tasks to account for the shortcomings of each individual classifier.

While this study focused on late fusion, an early fusion approach can be explored in the future. In addition, more products, including products that may not fall under the predefined categories, can be added to reduce overfitting. A better text classifier can be built with pre-trained bi-directional contextualized language models (Devlin et al. 2018). Transformers can be considered to replace CNNs and RNNs for both text and images (Vaswani et al. 2017; Wangperawong 2018; Niki Parmar 2018).

Finally, one possible extension to our work could be to build a vector representation of the products. Just as how word embeddings enabled us to more effectively classify text, a product embedding can be useful for capturing the relationship between products. Such a product embedding could help discover products that are "similar" for recommendation purposes and be used as input to a model to predict categories.

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