IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⪢ Impact Factor 8.066 ⪢ Peer-reviewed / Refereed journal ⪢ Vol. 10, Issue 7, July 2023

DOI: 10.17148/IARJSET.2023.107124

Transfer Learning and its application in E-Commerce

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Abstract: In machine learning, transfer learning has become a potent technique that enables models to use their previous knowledge and representations to perform better on new tasks or domains. By using pre-trained models that have acquired general features from massive datasets or comparable jobs, this strategy gets beyond the constraints of data availability and processing resources. several approaches to knowledge transfer between domains are provided by several forms of transfer learning, including inductive, transductive, unsupervised, semi-supervised, multi-task, and zero-shot transfer learning. Transfer learning has many uses in e-commerce, including fraud detection, product classification, and recommendation and picture search. This paper gives a thorough guide to classifying e-commerce products using transfer learning approaches, highlighting the advantages of knowledge transfer and the efficiency of fine-tuning models for particular use cases.

Keywords: transfer learning, e-commerce, image classification, text classification, data collection, fine tuning.

I. INTRODUCTION

Machine learning technique called transfer learning has lately achieved remarkable success. By applying the knowledge and representations gained from one job or domain to enhance performance on another task or domain, it circumvents the issue of limited data and computational resources. Although traditional machine learning technology has achieved great success and has been successfully applied in many practical applications, it still has some limitations for certain real-world scenarios. The ideal scenario of machine learning is that there are abundant labelled training instances, which have the same distribution as the test data. However, in many scenarios, collecting sufficient training data is often expensive, time-consuming, or even unrealistic. Semi-supervised learning can partly solve this problem by relaxing the need of mass labeled data. Typically, a semi-supervised approach only requires a limited number of labeled data, and it utilizes a large amount of unlabeled data to improve the learning accuracy. But in many cases, unlabeled instances are also difficult to collect, which usually makes the resultant traditional models unsatisfactory.

The fundamental tenet of transfer learning is that skills learned in one task or area can be applied to enhance learning or performance in a different activity or domain that is closely related. The model may generalize and adapt to new, unexplored data more quickly by transferring the learned representations[2].

Transfer learning, which uses data obtained by models trained on substantial datasets or comparable tasks, offers an alternative strategy. Instead of starting from scratch, pre-trained models provide a helpful starting point because they have already learnt general features and representations from a vast quantity of data.

Transfer learning can be done in a variety of ways, such as fine-tuning, domain adaptation, and multi-task learning. A pre-trained model is fine-tuned by retraining it on a smaller dataset relevant to the objective job. The model can adjust its learned representations to the variations of the new task via this technique. By addressing the variations in data distributions, domain adaptation, on the other hand, focuses on transferring knowledge across other domains. Multiple related tasks are simultaneously learned through multitasking, impacting.

II. TYPES OF TRANSFER LEARNING

Depending on the particular method employed, transfer learning can be divided into numerous forms. The main categories of transfer learning are as follows:

A. Inductive Transfer Learning:

The basic goal of inductive transfer learning is to move knowledge from a source domain with labeled data to a target domain with a related but different objective. To enhance learning and performance on the target task, the information gained from the source domain is used.

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B. Transductive Transfer Learning:

Learning through transductive transfer entails moving information from a labeled source domain to an unlabeled target domain. Utilizing the labeled data from the source domain is the goal in order to enhance predictions or classifications on the target domain. When using labeled data, this kind of transfer learning is beneficial.

C. Unsupervised Transfer Learning:

Unsupervised transfer learning involves transferring knowledge from a source domain to a target domain without relying on labeled data. Instead, the focus is on learning useful representations or features from the source domain that can be applied to the target domain. This type of transfer learning is particularly valuable when labeled data is scarce or entirely unavailable in both the source and target domains.

D. Semi-Supervised Transfer Learning:

Semi-supervised transfer learning, on the other hand, combines labeled data from the source domain with limited labeled data from the target domain. By transferring knowledge from the source domain, the model can enhance its learning and generalization capabilities on the target domain, even when labeled data in the target domain is limited, expensive, or time-consuming to acquire. This approach leverages the benefits of both labeled and unlabeled data to improve performance on the target task.

E. . Multi-Task Transfer Learning:

Multi-task transfer learning involves learning multiple related tasks simultaneously. By jointly learning these tasks, the model can leverage shared knowledge and representations, leading to improved performance on each individual task. The shared representations learned during multi-task training facilitate transfer learning between tasks and domains.

F. . Zero-Shot Transfer Learning:

Zero-shot transfer learning solves situations where the target task lacks labeled data. Instead, information from the source domain, where labeled data is present, is transferred to the target job to make predictions or make classifications. Without training data relevant to the target domain, this sort of transfer learning relies on understanding the link between the source and target domains to produce predictions.

These kinds of transfer learning offer various methods for utilizing information and models from a source domain to enhance performance on a target domain or activity. The availability of labeled data, the similarity of the domains, and the particular needs of the target task all play a role in the decision of transfer learning type.

III. APPLICATIONS OF TRANSFER LEARNING

Transfer Learning has demonstrated remarkable success across a wide range of domains. In computer vision, pre-trained models like ResNet, VGG, and inception have been utilized for various tasks, such as image classification, object detection, and image segmentation. In natural language processing ,models like BERT and GPT have significantly advanced tasks like sentiment analysis ,entity recognition ,and machine translation.

Some Applications include:

A. Finance:

Another area in which transfer learning can be applied is finance, such as in the area of car insurance risk estimations and financial early warning systems. Niculescu-Mizil and Caruana [3] presented an inductive transfer learning approach, which jointly learns multiple

Bayesian network structures instead of adaptive probabilistic net works from multiple related data sets. The authors examined the proposed method using car insurance risk estimation networks.

It is worth noticing that the works on intelligent financial warning systems and long term prediction in banking ecosystems [4-6] are the first systematic studies to apply transfer learning approaches using fuzzy logic techniques of computational intelligence to real-world financial applications to exploit the knowledge of the banking system, e.g., transferring the information.

B. Buisness Management:

Transfer learning has been applied in business management. For instance, Roy and Kaelbling proposed an efficient Bayesian task-level transfer learning to tackle the user's behavior in the meeting domain. Jin and Sun indicated that

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traditional neural network methods for traffic flow forecasting are based on a single task which cannot utilize information from other tasks. To take care of this type of challenge, multi-task based neural network is proposed to transfer knowledge to deal with traffic flow forecasting. Luis et al. proposed the use of a novel transfer Bayesian network learning framework, including structure and parameter learning, to handle a product manufacture process issue. Recently, Ma et al. studied the cross-company software defect prediction scenario in which the source and target data sets come from different companies, and proposed a novel transfer naive Bayes as the solution. A dynamic model for intelligent environments has been proposed to make use of the data from different feature spaces and domains with a novel fuzzy transfer learning process.

IV. TRANSFER LEARNING IS USED IN E-COMMERCE IN A VARIETY OF WAYS

E-commerce has changed the shopping experience by providing a hassle-free shopping experience and product delivery. It saves the customer's time and effort. It uses many strategies such as product recommendation, product classification, and optimizing other customer services. There are two major concerns- one at the seller side related to product categorization by providing proper labels and product pictures and the other at the customer side to search the product quickly with a better recommendation. The e-commerce system is vulnerable due to human errors. Any misclassification leads to other problems such as products not appearing in the search result, showing irrelevant recommendations, low sales or reduce sales, etc. from the perspectives of sellers and buyers[1]

A.Product Classification:

Transfer learning is applied in electronic commerce to categorize products into different categories. This is achieved by utilizing a pre-trained image classification model to extract relevant features from product images and then using these features to accurately categorize the products.

B.Product Recommendation:

Product Recommendations: In electronic commerce, transfer learning plays a significant role in providing personalized product suggestions to customers. By leveraging a pre-trained model that understands important features for predicting customer preferences, the accuracy of product recommendations can be improved based on their past purchase behavior and online browsing patterns.

C.Image Search:

Image search is the method of looking for products using images. By employing a pre-trained model to extract characteristics from product photographs and then using those features to search for related and similar images, transfer learning can be used to increase the accuracy of image search.

D.Fraud Detection:

Identifying fraudulent transactions process. By employing a pre-trained model to learn the attributes that are associated with fraudulent transactions, transfer learning can be utilized to increase the accuracy of fraud detection.

When there is little data available for the target job, transfer learning is an effective method for enhancing machine learning models' performance in e-commerce.

Some specific examples of how transfer learning is used in e-commerce:

1) Transfer learning can be used in Amazon to classify images of products. As they use a pre-trained model to extract features from product images and then use those features to classify the products into categories which helps Amazon to organize their products properly and to make it easier for customers to find the products they are looking for.

2) Netflix also uses transfer learning to recommend movies and TV shows to their customers as they use a pre-trained model to learn the features that are important for analysing customer choices. It helps Netflix to suggest movies and TV shows that customers enjoy.

3) Similarly,Google uses transfer learning to detect fraudulent transactions. They use a pre-trained model to know the features that are associated with fraudulent transactions. This helps Google to protect their customers from fraud.

Transfer learning is a powerful technique that is being used in a variety of ways in e-commerce. It is helping e-commerce businesses to improve their products, services, and customer experiences.

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V. CLASSIFYING E-COMMERCE PRODUCTS

Utilizing pre-trained models for both image and text processing is essential for classifying e-commerce items utilizing transfer learning and images and text. Here is a method for classifying products in e-commerce that blends transfer learning with image and text data:

A.Data Collection:
Assemble a database of labelled online items that contains both pictures of the items and textual descriptions of their features. Annotations for product categories or classes should be present in the dataset.

B.Image Feature Extraction:
Utilize a pre-trained convolutional neural network (CNN), such as VGG, ResNet, or Inception, that has been trained on a large-scale image dataset like ImageNet. Remove the fully connected layers of the pre-trained CNN and keep the convolutional layers. Use the pre-trained CNN to extract image features from the product images. The output of the last pooling or convolutional layer serves as the image representation.

C.Text Processing and representation:
Pre-process the textual descriptions or characteristics of the products. Do tokenization, remove the stop words, and apply techniques like appearing or lemmatization. Conversion of the already processed text into numerical representations, such as TF-IDF or word embeddings like Word2Vec or GloVe.

D.Fusion of Image and Text features:
Combine the extracted image features and the numerical representations of the textual data. You can concatenate these features into a single unified representation, allowing both image and text information to be considered together.

E.Transfer Learning:
Choose a transfer learning approach that allows you to leverage pre-trained models for both image and text. For image processing, use the pre-trained CNN as a feature extractor, keeping its convolutional layers frozen. Fine-tune the added fully connected layers or additional layers for the specific e-commerce classification task using the extracted image features.

F.Classification Model:
Combine the fused image and text features and feed them into a classification model, such as a multi-layer perceptron (MLP), support vector machine (SVM), or a deep neural network. Train the classification model using the labelled data, with the fused features as input, and the product categories as the target labels.

G.Model Evaluation and Fine Tuning:
Evaluate the trained model on a separate test dataset to assess its performance in classifying e-commerce products based on images and text. Fine-tune the model if necessary, by adjusting hyperparameters or modifying the architecture to optimize performance.

H.Deployment and Application:
By leveraging transfer learning with pre-trained models for both image and text processing, this approach enables a comprehensive and accurate classification of e-commerce products based on their visual and textual information. The transfer of knowledge from the pre-trained models improves the effectiveness and efficiency of the classification system, especially when dealing with limited labelled data in the e-commerce domain.

VI. CLASSIFYING E-COMMERCE PRODUCTS BASED ON IMAGES AND TEXT

For humans,classifying objects in an image is straightforward, as compared to machines. This process of classifying objects in an image, known as Image Classification involves labeling of images into predefined classes. Since there can be n number of classes into which an image can be classified, manual classification (when there are thousands of images) is difficult for humans too. That is why automating the process of object identification and classification with machines is gaining ground.

To make machines distinguish between the objects and classify them, computer vision, a subfield of Artificial Intelligence is used. Computer Vision is an AI technology that enables digital devices (face detectors, QR Code Scanners) to identify and process objects in videos and images, just like humans do.

DOI: 10.17148/IARJSET.2023.107124

The computer vision technology collaborates with Machine Learning (ML) that enables machines to learn and improve from experiences, without explicitly programmed for it. The models thus created using these technologies not only help in classifying images but gradually learns to give more accurate output with time.

There are different ways digital devices can be trained for image classification. Using machine learning with computer vision, several learning models can be created that help the machines to detect objects and classify them. Transfer learning is one of them.

In the later segment, we will discuss the transfer learning technique in detail. We will also discuss a real-time example of its implementation through one of the AI projects and understand the benefit that this model training technique offers.

A.*Image Classification using Transfer Learning Technique:*

Transfer learning is a timesaving way of building image identification models, introduced by W. Rawat & Z. Wang. With the transfer learning approach, instead of building a learning model from scratch, the model is made to learn from pre-trained models that have been trained on a large data set to solve a problem that is similar to the existing problem.
Consider this. A teacher has years of experience in a particular subject. Through his lectures, he transfers his knowledge to the students. Similar is the case with neural networks.

Neural networks are trained on data. The network (teacher) gains knowledge from the dataset, which is compiled as ‘weights’ of the network. In transfer learning, these weights can be extracted and transferred to other neural networks (students). So, instead of training a neural network from scratch, the learned features are transferred between the networks.

In this case, the developers proceed by removing the original classifier and adds a new classifier that fits the purpose. The model is then fine-tuned by following one of the following strategies:

1)Train the model from scratch: In this case, the architecture of the pre-trained model is used and model training is done according to the new dataset. Since the model here learns from scratch, a large dataset and computational power would be required by the model.

2)Train a few layers and leave others frozen: The lower layers of the model represent general features (which is generally problem independent) while the higher layers are feature specific (and problem-dependent as well). While the learnings are transferred from one data set to another, some of the layer weights are trained, while some of them remain frozen. Layer freezing, means the layer weights of a trained model remain unchanged when they are reused in a subsequent downstream task.

3)Freeze the convolutional base: In this case, the convolutional base is kept in its original form and its output is used to feed the classifier. Here, the pre-trained model is used as a feature extraction mechanism.

B.How Transfer Learning can be used in Different Scenarios:

Scenario 1: The data set is small but the data similarity is very high.

Since the data similarity is high, retraining the model is not required. The model can be repurposed by customizing the output layers as per the problem. Here, the pre-trained model is used as the feature extractor.

Scenario 2: The data set is small and the data similarity is low as well

When this is the case, the idea is to freeze the initial layers (say i) of the pre-trained model and train the remaining (n-i) layers. Since the data similarity is low, it is important to retrain the model and customize the higher layers of the model according to the new data set.

Scenario 3: The data size is large but the data similarity is low

When this is the case, the predictions made by the pre-trained model won’t be effective. Hence, it is recommended to train the neural network from scratch according to the new data.

Scenario 4: Size of data is large and the data similarity is high too

In this case, you have hit the jackpot. The pre-trained model is the most effective one and it would be great to retain the architecture and initial weights of the pre-trained model.

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C. *Text Classification using Transfer Learning Technique:*
Text classification in the context of e-commerce using transfer learning involves leveraging pre-trained language models to classify text data related to e-commerce products or services.

Transfer learning is a popular technique in natural language processing (NLP) that allows you to use knowledge gained from one task (e.g., general language understanding) to improve performance on a different, but related, task (e.g., e-commerce text classification).

Here's a step-by-step guide on how to approach e-commerce text classification using transfer learning:

1.*Data Collection and Preparation:*
Gather a large dataset of e-commerce text examples that need to be classified into specific categories or labels, such as product categories (electronics, clothing, books, etc.), sentiment (positive, negative, neutral), or product attributes (color, size, material, etc.).
Preprocess the text data by removing noise, stopwords, punctuation, converting text to lowercase, and performing tokenization.

2.*Selecting a Pre-trained Language Model:*
Choose a pre-trained language model that is suitable for your e-commerce text classification task. Models like BERT (Bidirectional Encoder Representations from Transformers), GPT (Generative Pre-trained Transformer), RoBERTa (A Robustly Optimized BERT), and XLNet are popular choices.

3.Fine-tuning the Language Model:
Initialize the chosen pre-trained model with its weights and architecture.
Add a classification head on top of the pre-trained model that suits your specific classification task. For example, for sentiment analysis, a single linear layer might suffice, while for multi-class product categorization, you might need a fully connected layer with softmax activation.

Train the modified model on your e-commerce dataset while keeping the pre-trained weights frozen for most layers (transfer learning step). This allows the model to retain the knowledge it learned from its original training.

4.Loss Function and Optimization:
Select an appropriate loss function for your specific task. For multi-class classification, the categorical cross-entropy loss is commonly used.
Choose an optimizer (e.g., Adam, SGD) and set hyperparameters like learning rate, batch size, and the number of epochs.

5.Model Evaluation:
Split your dataset into training, validation, and test sets.
During training, monitor the performance on the validation set to avoid overfitting.
After training, evaluate your model on the test set to assess its real-world performance.

6.Hyperparameter Tuning:
If the model's performance is not satisfactory, consider fine-tuning the hyperparameters or adjusting the architecture of the classification head.

7.Deployment:
Once you are satisfied with the model's performance, deploy it to a production environment for making predictions on new, unseen e-commerce text data.
Remember that the success of transfer learning depends on having a substantial amount of labeled data for fine-tuning. The more representative and diverse your e-commerce dataset is, the better the model can capture meaningful patterns and generalize well to new examples.

VII. CONCLUSIONS

Therefore through this study we can conclude saying that Transfer Learning is an efficient way to train AI models to recognize things and perform actions.Having learnt about the Transfer Learning and its application in E-Commerce and its various sectors like classifying products based on images and text ,we got to know more about Transfer Learning.

DOI: 10.17148/IARJSET.2023.107124

ACKNOWLEDGMENT

We are extremely grateful to our mentor **Mr Hrishikesh Mogare** for giving us the opportunity to explore a topic like Transfer Learning.

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