Do Better ImageNet Models Transfer Better... for Image Recommendation?

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ABSTRACT

Visual embeddings from Convolutional Neural Networks (CNNs) trained on the ImageNet dataset for the ImageNet Large Scale Visual Recognition Competition (ILSVRC) challenge have shown consistently good performance for transfer learning and are widely used in several tasks, including image recommendation. However, some important questions have not yet been answered in order to use these embeddings for a larger scope of recommendation domains: a) Do CNNs that perform better in ImageNet also work better for transfer learning in content-based image recommendation? b) Does fine-tuning help to improve performance? and c) Which is the best way to perform the fine-tuning?

In this paper we compare several CNN models pre-trained with the ImageNet dataset to evaluate their transfer learning performance to an artwork image recommendation task. Our results indicate that models with better performance in the ImageNet challenge do not always imply better transfer learning for artistic image recommendation tasks (e.g., NASNet vs. ResNet). Further analysis shows that fine-tuning can be helpful even with a small dataset, but not every fine tuning works.

Our results, although preliminary and focused on the art domain, can inform other researchers and practitioners on how to train their CNNs for better transfer learning towards image recommendation systems.

KEYWORDS

Recommender systems, Artwork Recommendation, Visual Features, Deep Neural Networks

1 INTRODUCTION

The outstanding results of Deep Convolutional Neural Networks (CNN) models in the area of computer vision since 2012 [8] as well as their performance for transfer learning to different datasets and tasks such as medical image classification [6] and image classification in small datasets [10] have made these models an important component in areas such as image-based recommendation. Several works in recommender systems [2, 4, 5, 9] have used CNNs such as AlexNet [8] or VGG [16] to automatically extract the features representing an image as a vector of visual features. This embedding is eventually used to train other models [4, 5] or to directly match and recommend similar images [2, 9]. However, an implicit assumption about these models is that the better they perform in the ImageNet Large Scale Visual Recognition Competition (ILSVRC) [14] in the ImageNet dataset, the better they will perform in other tasks. Kornblith et al. [7] challenged this assumption by evaluating the capacity of several state-of-the-art CNN models for transfer learning to different computer vision datasets. They showed that there is a rather small correlation between ImageNet performance and transfer learning performance when these CNNs are used solely as fixed feature extractors. All the models improved though after fine-tuning. The results provided important insights about using these CNNs models for transfer learning: always using the top performing model in the ILSVRC as a pre-trained visual feature extractor is not always the best idea. However, they did not test CNN visual transfer learning in an image recommendation task.

Objective. In this article, motivated by the experiments and results by Kornblith et al. [7], we study transfer learning for image recommendations. More particularly, we investigate whether the performance of a CNN model in the ImageNet dataset correlates with the results of recommending artwork images. Moreover, we experiment with two different fine-tuning alternatives (deep and shallow) to find out if we can improve the performance of the CNN when used solely as a feature extractor.

Research Questions. Our work was driven by the following research questions:

- **RQ1.** Are CNNs that perform better in ImageNet also better for transfer learning in content-based image recommendation?
- **RQ2.** Does fine-tuning help to improve the performance in the image recommendation task?
- **RQ3.** What is the best way to perform the fine-tuning?
We also show how to fine-tune the best of these pre-trained models with at least one of the aforementioned fields empty. We also implemented a method for selecting the best pre-trained models in order to boost its performance for a recommendation task. Our results are at the level of the state-of-the-art on content-based artwork recommendation [9].

2 DATASETS

2.1 UGallery

UGallery provided us with an anonymized dataset of 2,919 users, 6,040 items and 4,099 purchases (transactions) of paintings, where all users made at least one transaction. On average, each user has bought 2-3 items in the latest years. Each painting in this dataset is unique, so once an artwork is bought it is not available anymore to be recommended or to calculate recommendations based on co-occurrences, such as collaborative filtering [11, 13].

Metadata. Artworks in the UGallery dataset were manually curated by experts. In total, there are five attributes, but only two of these attributes are present in all paintings: medium (e.g., oil, acrylic), and artist. We use these attributes to fine-tune the pre-trained models described later in Section 3.

Visual Features. For each image representing a painting in the dataset we obtain features from CNN models described later in the Section 3.

2.2 Omniart

For some fine-tuning experiments we used the large art dataset Omniart [17], which originally reported of containing 432,217 artwork images, but has since grown to include more than 1 million data samples. Each data sample contains an image and metadata associated to it. These metadata include artwork name, artist full name, year of creation, collection origins, general type, artwork type, school and number of creators, among others.

In order to use this dataset for fine-tuning, we cleaned it, removing fields that were mostly empty. We then kept 3 fields: artist, artwork type and year of creation. Next, we filtered out every sample with at least one of the aforementioned fields empty. We also filtered out all the artworks by artists that appeared less than 100 times and we did the same for the artwork type. We ended up with 634,508 images, containing 2,080 different artists and 47 different artwork types. This dataset was then divided into train, validation and test sets in a proportion of 70%, 20% and 10% respectively.

3 METHODS

3.1 Transfer Learning

We experimented using some of the top performing CNNs models for the ImageNet challenge as presented in the updated list of Tensorflow-Slim, a high-level Tensorflow API for image classification [15]. The models selected for comparison in this article were VGG19 [16], ResNet50 [3], InceptionV3 [19], Inception-ResNetV2 [18] and NASNet [21].

As pointed out by Kornblith et al. [7], it is commonly assumed that the best performing CNN models in the ILSVRC challenge are also going to be the top performing models in other visual tasks. Following this assumption, we should expect NASNet to output the best embeddings for image recommendation. In the same work, Kornblith et al. [7] found that there is no perfect correlation between the performance of a model in the ILSVRC and in other visual tasks, as ResNet performs better than other models when using the pre-trained features obtained from it. We would like to find out if this result remains in our task of recommending art.

3.2 Fine-tuning

Beyond using each CNN solely as a pre-trained model for visual feature extraction and eventual transfer learning, we experimented with two different processes for fine-tuning the CNNs with the aim of improving their performance in artwork recommendation: shallow and deep fine-tuning. In addition, the fine-tuning could be performed by approaching single-task or multitask learning.

Our fine-tuning method is based on the work by Strezoski et al. [17], who propose a deep CNN that leverages multitask learning to extract features from artwork images. The model is flexible, and the same network can be adapted for single-task learning. As seen in Figure 1, our generic network model for fine-tuning is composed of three different parts which are stacked in the same order as presented. First, a base representation layer (Base Layer) acts as feature extractor. Our work is agnostic to the choice of this layer, but for the example we used ResNet50. Next, add a densely connected shared representation layer, of size 1,024. This layer is then connected to one-to-many output layers, one for each task used to train the network. The shared representation layer allows

![Figure 1: Generic model used for fine-tuning, adapted from Strezoski et al. [17].](image-url)

In the case of shallow tuning only the Shared Representation layer is updated. On the other side, for deep tuning, all the convolutional layers are tuned.

Contributions. Our work contributes to the area of transfer learning for image and image-based recommendation. We experiment with five pre-trained state-of-the-art CNN models for the ILSVRC competition. We also run simulated experiments to predict artwork purchases using a real-world transaction data provided by a popular online artwork store based in USA named UGallery. We also show how to fine-tune the best of these pre-trained models in order to boost its performance for a recommendation task. Our results are at the level of the state-of-the-art on content-based artwork recommendation [9].

Table 1: Results of different pre-trained embeddings at the artwork image recommendation task to the left (R:Recall, P:Precision), and their performance at the ILSVRC Challenge trained on ImageNet dataset (Acc: Accuracy). The top methods in both tasks do not correlate.

| CNN          | Artwork Image Recommendation | ILSVRC-2012-CLS |
|--------------|-----------------------------|-----------------|
|              | R@20 | P@20 | MRR@20 | mDCG@20 | Top-1 Acc. (%) | Top-5 Acc. (%) |
| ResNet50     | .1632 | .0141 | .0979  | .1255   | 75.2            | 92.2           |
| VGG19        | .1390 | .0124 | .0750  | .1008   | 71.1            | 89.6           |
| NASNet Large | .1379 | .0120 | .0743  | .0998   | 82.7            | 96.2           |
| InceptionV3  | .1332 | .0125 | .0744  | .1007   | 78.0            | 93.9           |
| Inception-ResNetV2 | .1302 | .0117 | .0692  | .0956   | 80.4            | 95.3           |
| Random       | .072  | .0013 | .0051  | .0093   | -               | -              |
we used an Adam optimizer for all of our training with a learning rate of 0.001 when training on the OmniArt Dataset, and 0.0001 when training on the UGallery dataset as this increases the performance on the prediction task. We used a validation set in order to prevent overfitting, and when the validation error did not decrease in 5 epochs we considered the training as complete.

4 RECOMMENDATION TASK: PREDICT PURCHASES

Our experimental protocol for evaluating image recommendation performance is based on our previous work [2, 9]. We predicted the items bought in each transaction of the dataset using the previous purchases of a customer to build a user model. We then provide recommendations by matching images in the UGallery dataset with the largest cosine similarity to the images in the user profile.

5 RESULTS

We first present the results of using pre-trained models for static visual feature extraction, in Table 1. Afterwards, we select the best performing model and proceed with the results about fine-tuning this model for image recommendation, in Table 2.

5.1 RQ1: Transfer Learning

Consistent with the results of Kornblith et al. [7], we find that there is no correlation between performance in ILSVRC trained with ImageNet and the actual image recommendation task, as clearly seen in Table 1. The top methods in ILSVRC are NASNet and Inception-ResNetV2, but in the artwork image recommendation task the top performing methods were ResNet and VGG19. ResNet also was the best pre-trained visual feature extractor in the series of experiments conducted by Kornblith et al. [7], which indicates the quality of this network embedding to transfer learning across different datasets and tasks. Subsequently, we use ResNet for the fine-tuning task presented next.

5.2 RQ2 & RQ3: Fine-Tuning

Table 2 presents the results of our fine-tuning and multitask experiments. We find that there is a significant influence on the dataset used, when using the actual dataset from which recommendations are going to be drawn. The performance of the method increased substantially evidenced by the top-3 best performances are achieved when fine-tuning with UGallery dataset.

Table 2: Results of the simulated recommendation experiment. Notice how a shallow fine-tuning of the ResNet model with the OmniArt dataset decreases the performance of the model, while a deep fine-tuning of all layers with the small UGallery dataset improves performance of ResNet and even further for the OmniArt model.

| CNN                              | R@20 | P@20 | F1@20 | MAP@20 | MRR@20 | nDCG@20 |
|----------------------------------|------|------|-------|--------|--------|---------|
| ResNet-deep-fine-tune-ugallery   | 1.954| 0.164| 0.0276| 0.0294 | 0.155  | 0.147   |
| ResNet-deep-fine-tune-ugallery-only-artist | 1.943| 0.166| 0.0279| 0.0300 | 0.166  | 0.1493  |
| Omniart-deep-fine-tune-ugallery  | 1.900| 0.159| 0.0266| 0.0267 | 0.0973 | 0.1330  |
| Omniart-shallow-only-period      | 1.632| 0.141| 0.0235| 0.0246 | 0.0979 | 0.1253  |
| Omniart-shallow-with-task-weights| 1.609| 0.134| 0.0224| 0.0227 | 0.0879 | 0.1147  |
| ResNet-shallow-fine-tune-ugallery-only-artist | 1.501| 0.137| 0.0230| 0.0242 | 0.0936 | 0.1202  |
| ResNet-shallow-fine-tune-ugallery| 1.541| 0.138| 0.0229| 0.0238 | 0.0942 | 0.1196  |
| ResNet-shallow-fine-tune-ugallery-only-medium | 1.541| 0.138| 0.0225| 0.0238 | 0.0894 | 0.1165  |
| Omniart-shallow-only-type        | 1.510| 0.127| 0.0212| 0.0217 | 0.0831 | 0.1092  |
| Omniart-shallow-no-task-weights  | 1.473| 0.129| 0.0214| 0.0234 | 0.0906 | 0.1150  |
| Omniart-shallow-only-artist      | 1.442| 0.129| 0.0213| 0.0235 | 0.0898 | 0.1153  |
| ResNet-shallow-fine-tune-ugallery-only-medium | 1.374| 0.124| 0.0204| 0.0218 | 0.0856 | 0.1101  |
| Omniart-shallow-only-period      | 0.937| 0.081| 0.0135| 0.0127 | 0.0514 | 0.0689  |
| Random                          | 0.072| 0.013| 0.0022| 0.0014 | 0.0051 | 0.0093  |

the model to learn a rich representation that is useful to each of the tasks learned. After fine-tuning, we will extract the image visual features used for recommendation based on the activation of the shared representation layer.

To train the model, we stage a supervised task based on one of our two datasets. This supervised task consists in predicting the artist, type, medium, etc. labeled in the artwork image. Each output layer focuses on one task, and the loss that is used depends on the task type: Cross Entropy for classification tasks (such as artist and type prediction), and MAE for regression tasks (such as period in the OmniArt dataset [17]).

**Shallow Fine-tuning.** In this fine-tuning method we keep the base layer frozen at training time, so we only adjust the weights of the shared representation layer. Thus, we use the output of the pre-trained network as features of the image, without re-training it.

Deep Fine-tuning. Based on the insight given by Kornblith et al. [7] as well as previous works on the medical image domain [20], we update all the weights in the base layer, shown in Figure 1. The aforementioned works indicate that a deep fine-tuning usually increases a model performance when transferring to other classification tasks, and even with a small dataset the improvement can be significant.

**Single task vs. multitask learning.** We experimented using multiple tasks. The argument for pursuing multitask learning lies in the expectation of learning more flexible embedding than single-task learning, since the same representation must be useful to solve several tasks. Then, for our multitask learning approaches, our loss functions are inspired by a simplified version of the one used by Strezoski et al. [17]. Being $L$ the cumulative loss for all tasks, $L_i$ the loss for task $i$ and $w_i$ the weight associated to task $i$, as a way to increase the importance of any given task, the multitask loss is:

$$L = \sum_{i=0}^{N} w_i \ast L_i \quad (1)$$

3.3 Training

We used an Adam optimizer for all of our training with a learning rate of 0.001 when training on the OmniArt Dataset, and 0.0001 when training on the UGallery dataset as this increases the performance on the prediction task. We used a validation set in order to prevent overfitting, and when the validation error did not decrease in 5 epochs we considered the training as complete.

$$L_i = w_i \ast L_i$$
Surprisingly, the use of a larger dataset of artwork images with metadata, such as Omniant, does not help in the recommendation task, and even decreases the performance if not fine-tuned with UGallery. This might be explained because of important differences between the samples from both the training dataset (Omniant) and the recommendation dataset (UGallery). For instance, the latter contains more modern and abstract artworks, and the former contains pictures, masks, sculptures, and pottery. Filtering out types other than paintings remains for a future work to explore.

Also consistent with the results of Kornblith et al. [7], we found that the performance of a shallow fine-tuning is significantly lower than the performance achieved when using deep fine-tuning. All of the top performing methods are achieved using this fine-tuning variant.

Moreover, when artist was the target of the learning task, we did not find significant differences between multitask and single-task learning. However, we identified a significant difference when the learning task includes the targets period or medium. The latter achieved a lower performance most of the time. This result could be explained by the distributions of mediums types in the UGallery dataset, since more than 60% of the artworks belong to the medium type oil painting. Hence, learning this classification might provide little information about personal user preference.

6 CONCLUSIONS
In this paper, motivated by the previous works of Kornblith et al. [7] in transfer learning, as well as Strezoski and Worrying [17] research on multitask learning for art images, we have studied whether the accuracy of several top-performing pre-trained models in the ImageNet dataset correlates with their transfer learning capacities for image recommendation. Our results indicate that there is no clear correlation, and that a neural model like ResNet performs better for transfer learning to image recommendation compared to NASNet of InceptionResNetV2, which performs better in the ILSVRC task.

Using ResNet as our base model, we also tested several fine-tuning alternatives to improve the performance of the pre-trained CNN model. We found that a deep fine-tuning (rather than a shallow fine-tune) along with the same target dataset UGallery (rather than the larger but noisy Omniant), can significantly improve the performance of the recommendations evaluated in several metrics. With respect to multitask vs. single-task learning, there was no a clear winner, but results seem to indicate that learning an embedding that discriminates between artists can be helpful for predicting artistic image preferences.

Our results are good, improving our best performance in this task in [2], and have the advantage of not relying on the metadata of the artwork, just on the image. This combined with the current tooling that has been developed [1][12] for the use of deep models makes this approach very convenient.

In future work we expect to test the fine-tuning performance of all the pre-trained models (not only ResNet). Moreover, we will test other datasets in an attempt to generalize our results to other domains of image recommendation beyond art. Finally, we will attempt to test different neural network architectures to learn user preferences, such as a siamese network or one supporting the triplet loss.

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REFERENCES
[1] François Chollet. 2015. Keras. https://github.com/fchollet/keras. (2015).
[2] Vicente Dominguez, Pablo Messina, Denis Parra, Domingo Mery, Christoph Trattner, and Alvaro Soto. 2017. Comparing Neural and Attractiveness-based Visual Features for Artwork Recommendation. In Proceedings of the Workshop on Deep Learning for Recommender Systems, co-located at RecSys 2017.
[3] Kaming He, Xiangyi Zhang, Shaqing Ren, and Jian Sun. 2015. Deep Residual Learning for Image Recognition. (2015). http://arxiv.org/abs/1512.03385
[4] Ruining He, Chen Fang, Zhaowen Wang, and Julian McAuley. 2016. VISTA: A Visually, Socially, and Temporally-aware Model for Artistic Recommendation. In Proceedings of the 10th ACM Conference on Recommender Systems (RecSys ’16). ACM, New York, NY, USA, 309–316.
[5] Ruining He and Julian McAuley. 2016. VIBR: visual Bayesian Personalized Ranking from implicit feedback. In Proceedings of the Thirteenth AAAI Conference on Artificial Intelligence. AAAI Press, 144–150.
[6] Shin Hoo-Chang, Holger R. Roth, Minchung Gao, Le Lu, Ziyue Xu, Isabella Nogues, Jianhua Yao, Daniel Mollura, and Ronald M Summers. 2016. Deep convolutional neural networks for computer-aided detection. CNN architectures, dataset characteristics and transfer learning. IEEE transactions on medical imaging 35, 5 (2016), 1245.
[7] Simon Kornblith, Jonathon Shlens, and Quoc V. Le. 2018. Do Better ImageNet Models Transfer Better? (2018). http://arxiv.org/abs/1805.08974
[8] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems. 1097–1105.
[9] Pablo Messina, Vicente Dominguez, Denis Parra, Christoph Trattner, and Alvaro Soto. 2018. Content-Based Artwork Recommendation: Integrating Painting Metadata with Neural and Manually-Engineered Visual Features. User Modeling and User-Adapted Interaction (2018).
[10] Maxime Oquab, Leon Bottou, Ivan Laptev, and Josef Sivic. 2014. Learning and transferring mid-level image representations using convolutional neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition. 1717–1724.
[11] Denis Parra and Shaghayegh Sahelbi. 2013. Recommender systems: Sources of knowledge and evaluation metrics. In Advanced techniques in web intelligence-2 Springer, 149–175.
[12] Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. 2017. Automatic differentiation in PyTorch. (2017).
[13] Paul Resnick, Neophytoos Iacouvo, Mitesh Suchak, Peter Bergstrom, and John Riedl. 1994. GroupLens: an open architecture for collaborative filtering of netnews. In Proceedings of the 1994 ACM conference on Computer supported cooperative work. ACM, 175–186.
[14] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. 2015. ImageNet Large Scale Visual Recognition Challenge. International Journal of Computer Vision (IJCV) 115, 3 (2015), 211–252.
[15] Nathan Silberman and Sergio Guadarrama. 2016. TensorFlow-Slim image classification model library. https://github.com/tensorflow/models/tree/master/research/slim (2016). [Online; accessed 20-July-2018].
[16] Karen Simonyan and Andrew Zisserman. 2014. Very Deep Convolutional Networks for Large-Scale Image Recognition. (2014). http://arxiv.org/abs/1409.1556
[17] Gjorgi Strezoski and Marcel Worringer. 2017. Omniant: multi-task deep learning for artistic data analysis. arXiv preprint arXiv:1708.08684 (2017).
[18] Christian Szegedy, Sergey Ioffe, and Vincent Vanhoucke. 2016. Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning. (2016). http://arxiv.org/abs/1602.07261
[19] Christian Szegedy, Sergey Ioffe, and Vincent Vanhoucke. 2016. Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning. (2016). http://arxiv.org/abs/1602.07261
[20] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. Imagenet classification with deep convolutional neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition. 1717–1724.
[21] Barret Zoph, Vijay Vasudevan, Jonathon Shlens, and Quoc V. Le. 2017. Learning Transferable Architectures for Scalable Image Recognition. (2017). http://arxiv.org/abs/1707.07012