

Introduction to Transfer Learning

Classifying Photographs vs. Drawings



Overview

Problem

Here we show how to develop a deep learning algorithm to classify images given any small labeled dataset. To demonstrate the procedure, we train a classifier to identify whether an input image is photograph of a real object or whether it is a painting/drawing. We use a technique called transfer learning to do this.

Transfer Learning

Humans are able to learn very quickly to identify something after being shown only a few examples because we can utilize our existing knowledge about the world to solve new problems. This ability to transfer knowledge learned for one task in one domain to another task in a different domain is called transfer learning.

Typically machine learning algorithms do not generalize well to situations very different from the data that is used for training. Furthermore, they typically require large amounts of labeled data to achieve good performance when trained from the ground up.

However, convolutional neural nets trained on images learn to detect simple feature such as edges, corners, color blobs, etc., in their early layers. These features are useful for all kinds of image processing tasks. Therefore, we can reuse these nets already trained on a large dataset of images such as ImageNet, and fine-tune them to build a classifier for a new problem using only a few labeled elements.

Data

A dataset of photographs and drawings can be easily obtained by searching on the web (e.g. Google Image Search) or using the function `WebImageSearch`. Here, we have already scraped some photographs and drawings and shown below.

Photos

Getting 150 images of photographs by partitioning the image below and labeling each of them "Photo".

```
photos = Flatten@ImagePartition[
```



```
, {224, 224}] → "Photo" // Thread;
```

Drawings

Getting 150 images of drawings from the image below and labeling them "Drawing".

```
drawings = Flatten@ImagePartition[
```



```
, {224, 224}] → "Drawing" // Thread;
```

Splitting into Training and Testing Data

Randomly shuffling and then splitting the dataset into 200 images for training and 100 images for testing.

```
{trainingData, testData} = TakeDrop[RandomSample@Join[drawings, photos], 200];
```

Having a separate test set is essential since it ensures that the algorithm is not simply memorizing the image shown to it without generalizing to unseen images.

Designing Net

Pre-trained Net Model

We download the convolutional neural net used in ImageIdentify(<https://www.imageidentify.com>), which is already trained on millions of images to classify objects belonging to thousands of different classes.

```
preTrainedNet = NetModel["Wolfram ImageIdentify Net for WL 11.1"]
```

		image
	Input	3-tensor (size: $3 \times 224 \times 224$)
conv_1	ConvolutionLayer	3-tensor (size: $64 \times 112 \times 112$)
bn_1	BatchNormalizationLayer	3-tensor (size: $64 \times 112 \times 112$)
relu_1	Ramp	3-tensor (size: $64 \times 112 \times 112$)
pool_1	PoolingLayer	3-tensor (size: $64 \times 55 \times 55$)
conv_2_red	ConvolutionLayer	3-tensor (size: $64 \times 55 \times 55$)
bn_2_red	BatchNormalizationLayer	3-tensor (size: $64 \times 55 \times 55$)
relu_2_red	Ramp	3-tensor (size: $64 \times 55 \times 55$)
conv_2	ConvolutionLayer	3-tensor (size: $192 \times 55 \times 55$)
bn_2	BatchNormalizationLayer	3-tensor (size: $192 \times 55 \times 55$)
relu_2	Ramp	3-tensor (size: $192 \times 55 \times 55$)
pool_2	PoolingLayer	3-tensor (size: $192 \times 27 \times 27$)
NetChain [3a	NetGraph[<<23>>]	3-tensor (size: $256 \times 27 \times 27$)
3b	NetGraph[<<23>>]	3-tensor (size: $320 \times 27 \times 27$)
3c	NetGraph[<<17>>]	3-tensor (size: $576 \times 14 \times 14$)
4a	NetGraph[<<23>>]	3-tensor (size: $576 \times 14 \times 14$)
4b	NetGraph[<<23>>]	3-tensor (size: $576 \times 14 \times 14$)
4c	NetGraph[<<23>>]	3-tensor (size: $608 \times 14 \times 14$)
4d	NetGraph[<<23>>]	3-tensor (size: $608 \times 14 \times 14$)
4e	NetGraph[<<17>>]	3-tensor (size: $1056 \times 7 \times 7$)
5a	NetGraph[<<23>>]	3-tensor (size: $1024 \times 7 \times 7$)
5b	NetGraph[<<23>>]	3-tensor (size: $1024 \times 7 \times 7$)
global_pool	PoolingLayer	3-tensor (size: $1024 \times 1 \times 1$)
linear	LinearLayer	vector (size: 4315)
softmax	SoftmaxLayer	vector (size: 4315)
	Output	class

This is a convolutional neural network architecture called Inception, which is very fast to train and evaluate.

Truncating Net

The number of neurons in the final linear layer should be equal to the number of classes of objects. Therefore, we remove the layers at the end which were designed to perform classification on over 4000 images. This truncated net is known as a feature-extractor since it maps any input image into a vector of real numbers encoding useful properties about the image.

```
truncatedNet = Take[preTrainedNet, {1, -3}]
```

NetChain [Input	image
			3-tensor (size: 3 × 224 × 224)
	conv_1	ConvolutionLayer	3-tensor (size: 64 × 112 × 112)
	bn_1	BatchNormalizationLayer	3-tensor (size: 64 × 112 × 112)
	relu_1	Ramp	3-tensor (size: 64 × 112 × 112)
	pool_1	PoolingLayer	3-tensor (size: 64 × 55 × 55)
	conv_2_red	ConvolutionLayer	3-tensor (size: 64 × 55 × 55)
	bn_2_red	BatchNormalizationLayer	3-tensor (size: 64 × 55 × 55)
	relu_2_red	Ramp	3-tensor (size: 64 × 55 × 55)
	conv_2	ConvolutionLayer	3-tensor (size: 192 × 55 × 55)
	bn_2	BatchNormalizationLayer	3-tensor (size: 192 × 55 × 55)
	relu_2	Ramp	3-tensor (size: 192 × 55 × 55)
	pool_2	PoolingLayer	3-tensor (size: 192 × 27 × 27)
	3a	NetGraph[<<23>>]	3-tensor (size: 256 × 27 × 27)
	3b	NetGraph[<<23>>]	3-tensor (size: 320 × 27 × 27)
	3c	NetGraph[<<17>>]	3-tensor (size: 576 × 14 × 14)
	4a	NetGraph[<<23>>]	3-tensor (size: 576 × 14 × 14)
	4b	NetGraph[<<23>>]	3-tensor (size: 576 × 14 × 14)
	4c	NetGraph[<<23>>]	3-tensor (size: 608 × 14 × 14)
	4d	NetGraph[<<23>>]	3-tensor (size: 608 × 14 × 14)
	4e	NetGraph[<<17>>]	3-tensor (size: 1056 × 7 × 7)
	5a	NetGraph[<<23>>]	3-tensor (size: 1024 × 7 × 7)
	5b	NetGraph[<<23>>]	3-tensor (size: 1024 × 7 × 7)
	global_pool	PoolingLayer	3-tensor (size: 1024 × 1 × 1)
		Output	3-tensor (size: 1024 × 1 × 1)

Attaching Classifier

Now we create a new net by attaching 2 neurons and a Softmax layer to create a classifier for two classes. The softmax layer ensures that probabilities of each class is the output. We attach a NetDecoder to the output to convert the probabilities to the class names.

```
net = NetChain[{truncatedNet, 2, SoftmaxLayer[]},
  "Output" → NetDecoder[{"Class", {"Photo", "Drawing"}}]]
```

NetChain [Input	image 3-tensor (size: $3 \times 224 \times 224$)]
1	NetChain[<<22>>]		3-tensor (size: $1024 \times 1 \times 1$)	
2	LinearLayer		vector (size: 2)	
3	SoftmaxLayer		vector (size: 2)	
		Output	class (uninitialized)	

This net takes an image as input and outputs a class which is either “Photo” or “Drawing”.

Training

Now we train this new net on our dataset. This procedure is called *fine-tuning* since the net contains weights already pre-trained on a larger dataset.

Net Train

```
trainedNet = NetTrain[net, trainingData, TargetDevice → "GPU"]
```

NetChain [Input	image 3-tensor (size: $3 \times 224 \times 224$)]
1	NetChain[<<22>>]		3-tensor (size: $1024 \times 1 \times 1$)	
2	LinearLayer		vector (size: 2)	
3	SoftmaxLayer		vector (size: 2)	
		Output	class	

Using a GPU speeds up the training by over 15x. If a GPU is not available, the `TargetDevice` option can be removed or set to “CPU”.

Testing

Classifier Measurements

Computing performance of the fine-tuned net model.

```
cm = ClassifierMeasurements[trainedNet, testData]
```

ClassifierMeasurementsObject [	Classifier: Net]
			Number of test examples: 100	
			Number of classes: 2	
			Accuracy: 0.9300 ± 0.026	

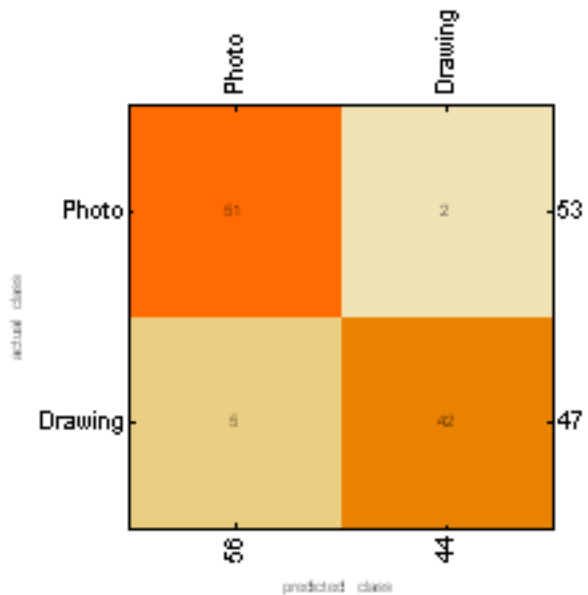
The accuracy is also shown above in the `ClassifierMeasurementsObject`. This is an object from which

you can query all kinds of properties about how the model performs on the test set.

Confusion Matrix

A confusion matrix shows the distribution of predictions on the test set across each class. The diagonal entries show the number of correctly classified elements.

```
cm["ConfusionMatrixPlot"]
```



Misclassified Examples

All the examples in the test set which were classified incorrectly are shown below.

```
cm["MisclassifiedExamples"][[;;, 1]] // GraphicsRow
```



Comparisons

Net Train without Transfer Learning

We reset the net model with random initialization to erase the pre-trained knowledge. Then we train the net in the same manner as before for comparison.

```
trainedNet = NetTrain[NetInitialize[net, All], trainingData, TargetDevice → "GPU"]
```

NetChain [image
1	Input	3-tensor (size: $3 \times 224 \times 224$)
2	NetChain[<<22>>]	3-tensor (size: $1024 \times 1 \times 1$)
3	LinearLayer	vector (size: 2)
	SoftmaxLayer	vector (size: 2)
Output		class

Computing accuracy on the test set.

```
cm = ClassifierMeasurements[trainedNet, testData]
```


```
ClassifierMeasurementsObject [  Classifier: Net  
Number of test examples: 100  
Number of classes: 2  
Accuracy: 0.730 ± 0.045 ]
```

We can see that without transfer learning the net model performs much worse than before on the same dataset.

Classify with Raw Pixels

Training the built-in Classify functions on a vector of raw pixels without using any feature extractors for images.

```
classifyRaw =  
Classify[MapAt[Flatten@*ImageData, trainingData, {;;, 1}], PerformanceGoal → "Quality"]
```

```
ClassifierFunction [  Input type: NumericalSequence  
Classes: Drawing, Photo  
Method: NaiveBayes  
Number of training examples: 200 ]
```

Computing the accuracy with the raw pixels as inputs for each image in the test set.



```
ClassifierMeasurements[classifyRaw, MapAt[Flatten@*ImageData, testData, {;;, 1}]]
```

```
ClassifierMeasurementsObject [  Classifier: NaiveBayes  
Number of test examples: 100  
Number of classes: 2  
Accuracy: 0.8300 ± 0.038 ]
```

Classify with Image Features

Training Classify on the same training set, which by default uses a built-in feature extractor for images.


```
classifyFeatures =
  Classify[trainingData, FeatureExtractor → "ImageFeatures", PerformanceGoal → "Quality"]
```

ClassifierFunction [  Input type: Image
Classes: Drawing, Photo
Method: RandomForest
Number of training examples: 200]

Computing the accuracy on the same test set.

```
ClassifierMeasurements[classifyFeatures, testData]
```

ClassifierMeasurementsObject [  Classifier: RandomForest
Number of test examples: 100
Number of classes: 2
Accuracy: 0.8600 ± 0.035]

We achieve a slightly higher accuracy with the built-in Classify function. This is because Classify internally uses a pre-trained net model to extract features from the images before training the classifier. The difference is that we have fine-tuned every layer in the net, whereas Classify trains a machine learning algorithm on the outputs of the net, keeping each layer fixed.

Conclusion

We have introduced the concept of transfer learning and demonstrated how it can be used for the simple problem of classifying whether an input image is a photograph or not. We achieved 93% accuracy with a small training dataset containing only 100 images of each class. Furthermore, we show that the transfer learning achieves significantly better results compared to training the net from scratch or using other machine learning methods.

This technique can be applied to many kinds of image classification problems, even when the new dataset is completely different from the original dataset used to pre-train the net models.

Further reading: <https://cs231n.github.io/transfer-learning/>