ATTENTION FOR FINE-GRAINED CATEGORIZATION

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ABSTRACT

This paper presents experiments extending the work of Ba et al. (2014) on recurrent neural models for attention into less constrained visual environments, beginning with fine-grained categorization on the Stanford Dogs data set. In this work we use an RNN of the same structure but substitute a more powerful visual network and perform large-scale pre-training of the visual network outside of the attention RNN. Most work in attention models to date focuses on tasks with toy or more constrained visual environments. We present competitive results for fine-grained categorization. More importantly, we show that our model learns to direct high resolution attention to the most discriminative regions without any spatial supervision such as bounding boxes. Given a small input window, it is hence able to discriminate fine-grained dog breeds with cheap glances at faces and fur patterns, while avoiding expensive and distracting processing of entire images. In addition to allowing high resolution processing with a fixed budget and naturally handling static or sequential inputs, this approach has the major advantage of being trained end-to-end, unlike most current approaches which are heavily engineered.

1 INTRODUCTION

This work presents experiments extending the work of Ba et al. (2014) to less constrained visual environments, beginning with fine-grained categorization. Ba et al. (2014) tackles the challenging problem of sequence prediction in simplified visual settings (MNIST and Street View House Numbers) using a recurrent model of attention similar to Mnih et al. (2014). Complementary to that work, we are addressing the simpler task of classification but in a visual environment with significant clutter and occlusion, variations in lighting and pose, and a more difficult class discrimination task. Previous work in learned visual attention models have tackled a number of computer vision problems and demonstrated the benefits of various attention mechanisms, though most of the work focuses on toy or more constrained environments, such as detecting simple shapes (Schmidhuber & Huber, 1991), tasks based on MNIST digits (Larochelle & Hinton, 2010; Bazzani et al., 2011; Denil et al., 2012; Ranzato, 2014; Mnih et al., 2014), the vision-control game of “catch” (Mnih et al., 2014), expression classification for 100 × 100 aligned faces (Larochelle & Hinton, 2010; Zheng et al., 2014), detection of frontal faces (Tang et al., 2013), tracking of hockey players (Bazzani et al., 2011; Denil et al., 2012) and gesture recognition (Darrell & Pentland, 1996). Most recently, two papers have presented an attention-like model for detection of chairs, people, cars, doors, and tables from SUN2012 images (Xiao et al., 2010); Xu et al. (2015) applies two different neural network visual attention models to the task of caption generation for MSCOCO images (Lin et al., 2014).

Recent computer vision literature leverages the supervised form of visual attention for object detection (Szegedy et al., 2014a,b) or fine-grained category detection (Zhang et al., 2014). By first localizing promising regions and then running a full-blown classification model on each of these regions, these models are somewhat similar to our attention approach in that their focus on relatively high resolution regions. These systems however are somewhat engineered, cannot aggregate evidence from diverse image regions, cannot refine and disambiguate judgments over time and lack the benefits end-to-end trained systems like ours have. Additionally, they heavily rely on the presence of spatial supervision (bounding boxes) while our attention model discovers important features on its own. This is particularly advantageous in computer vision where supervised data critical but scarce.
Figure 1: Three classes from the Dogs data set that are difficult to tell apart due to high intra-class variability and high similarity across classes. The lines show the class boundaries; the classes are Eskimo Dog on the left, Malamute in the center, and Siberian Husky on the right. Of the 120 classes in Stanford Dogs, our model performs worst on Siberian Husky.

We apply the visual attention model from Ba et al. (2014) to the Stanford Dogs fine-grained categorization task (Khosla et al., 2011), choosing to perform the task without using the provided bounding boxes for training or testing. This amounts to learning to simultaneously localize and classify objects within scenes despite difficult class boundaries, large variations in pose and lighting, varying and cluttered backgrounds, and occlusion (Figure 1). Fine-grained categorization is a natural proving ground for attention-based models. When performing classification at the sub-category level, e.g. German Shepherd versus Poodle, the background is often uncorrelated with class and acts as a distraction to the primary task. As a result, several hand-crafted vision pipelines use provided bounding boxes to isolate the object of interest or may perform segmentation of the object from the background, e.g. Parkhi et al. (2011); Chai et al. (2013); Angelova & Zhu (2013). Attention models could address this challenge by learning to focus processing and discriminatory power on the parts of the image that are relevant for the task. In addition to ignoring the distractors in the image, a good attention model could learn to focus processing power on the specific features of the objects that help to tell them apart, for example the face, ears, and tail for dogs. Future versions of this model could potentially also choose the scale at which to examine details.

2 MODEL DESCRIPTION

The structure of our model is nearly the same as that presented in Ba et al. (2014) with a few differences; we give an overview of the model here and describe the ways in which our model differs. We refer the reader to that work for a more in-depth description of the network choices and training procedure.

Figure 2 shows the structure of the model. The system as a whole takes as input an image of any size and outputs N-way classification scores using a softmax classifier, which is a very similar task to the finding digits and digit addition tasks in Ba et al. (2014). The model is a recurrent neural network, with N steps that correlate with N “glimpses” into the input image. At step \( n \), the model receives row and column coordinates \( l_{n-1} \), which describe a point in the input image. The network extracts a multi-resolution patch from the input image at those coordinates, passes the pixels through fully-connected layers which combine with activations from the previous glimpse step, and either outputs coordinates \( \hat{l}_n \) for the next glimpse or a final classification \( y_s \).

The structure of the glimpse images is shown in Figure 3. Each glimpse is a multi-resolution image created by extracting patches at varying sizes, resizing them all to 96 x 96, and concatenating them side-by-side. The goal is to emulate a “foveal” structure with the sharpest part of the image in the center and lower resolution toward the periphery. The top row shows glimpses for a 2-resolution model and the bottom row for a 3-resolution model. The high-resolution patch is extracted from a...
Figure 2: Diagram of the model. The grayed-out boxes denote resolutions not in use; in our experiments the context is always a low-resolution patch, while each glimpse can be any combination of the low-, medium-, and high-resolution patches.

Figure 3: Visualizations of 2-resolution (a) and 3-resolution (b) glimpses on an image from our validation set, with learned fixation points. For each the glimpse images are in order, from top to bottom, and the box diagram corresponds to the second glimpse. The composite image is created from all three glimpses. The context image is not shown but is always the same resolution and size as the low-resolution glimpse patches shown in (b).

square that is a fixed size for a given image (more on scale selection below). The medium-resolution patch is from a square that is twice the length on a side of the high-resolution patch, and the low-resolution patch is twice the size of the medium-resolution patch on a side. For example, if the high resolution patch is $100 \times 100$, then the medium- and low-resolution patches are $200 \times 200$ and $400 \times 400$, respectively. Where an extraction box extends off the edge of the image, we fill the pixels with random noise. Figure 3 shows composite images which are a helpful visualization to understand what pixels the network sees, though it is not presented with them in this form; these images are generated from the glimpse pixels by displaying at each pixel the highest-resolution pixel available in any glimpse, and any pixels not captured by the glimpses are filled with noise.
The model begins processing from a “context image”, which is a square low-resolution patch from the input image that is the same size as our low-resolution glimpse patch. The location of the context image is chosen randomly in training but is centered during inference. The context image is used by layer \( r^{(2)}_n \) to produce the first glimpse location \( l_0 \) and can influence the selection of subsequent glimpse locations through the recurrent connections between the \( r^{(2)}_n \) layers along the “top deck” of the model, however the double-decker structure prevents the context image from having a pathway to the classifier except through the \( l_n \) coordinates. See \cite{ba2014multiple} for more discussion about this design choice. In training, the \( r^{(2)}_n \) layers that produce the \( l_n \) coordinates are trained with a mix of backpropagation from the connection to layer \( r^{(1)}_{n+1} \) and a policy gradient update. See \cite{ba2014multiple} for details.

There are four major differences between our system and the classification-type models from \cite{ba2014multiple}. First, there is wide variation in image size across our data set, however the size of the objects scales with the image size most of the time. To be robust to input image size, our multi-resolution patches are sized relative to the input image. In our experiments, a side of the high-resolution square patch is \( 1/4 \) the shorter dimension of the input image, making the sides of the medium- and low-resolution patches \( 1/2 \) and the full length of the image’s short side, respectively.

Second, we use a “vanilla” RNN instead of an LSTM, where \( r^{(1)}_n \) and \( r^{(2)}_n \) at glimpse \( n \) each consist of 4,096 nodes, and \( r_{n}(i) \) is fully-connected to \( r_{n+1}(i) \) for \( i = 1, 2 \). Third, instead of element-wise multiplying the outputs of the glimpse visual core \( G_{image}(x_n|W_{image}) \) and \( G_{loc}(l_n|W_{loc}) \), our model linearly combines them by concatenating their outputs and passing through a fully-connected layer. Future experiments will incorporate both of these variations.

The final and largest difference is that we replace the visual glimpse network \( G_{image}(x_n|W_{image}) \) described in \cite{ba2014multiple} with a more powerful visual core based on the “GoogLeNet” model \cite{szegedy2014going} that won the ILSVRC 2014 classification challenge \cite{russakovsky2014imagenet}. We start from a GoogLeNet model that we pre-trained on the ImageNet 1000-way task on a subset of the ILSVRC 2012 training data (more on our use of this data set below). We don’t use the full GoogLeNet model within the attention model, however; the full model is designed for \( 224 \times 224 \) inputs and if applied to \( 96 \times 96 \) subsampling and pooling layers cause the final output to be too small for our purposes. To remedy this, we chop off the last two “inception” layers, skipping 5 convolutional layers and an average-pooling layer. The full depth could be kept by removing some pooling layers, and we will study the effect of different architectures, including shallower ones, in future work.

We then fine-tune the visual network outside of the RNN model on ILSVRC images using random multi-scale patches as input and targeting the ImageNet 1000-way classification labels. In this stage of training, we replicate the visual model for each input scale, yielding 3 “towers” which share parameters, and join their outputs in different combinations with depth concatenating layers (Figure 4). All towers are jointly trained by back-propagating error from multiple 1000-way softmax classifiers (called “heads”) as shown in the figure. This multi-headed training model ensures each tower remains independently relevant even if another tower is more informative. We have found that if taken independently, the lowest-resolution patch typically yields best results and learning might rely on it solely otherwise.

During training of the attention model, we remove all training heads and take the output of the depth concatenation of multiple towers as glimpse input as shown in Figure 4. For this work, we hold the visual core’s parameters fixed during attention model training.

In all stages of training for the attention RNN and our experimental baselines, we use a subset of the ILSVRC 2012 training set from which we removed the Stanford Dogs test images as well as the Dogs images that we use for validation. We refer to this in our experimental section as the “de-duped” ILSVRC data set. We saw a drop of 3% in the accuracy of the full GoogLeNet baseline model when trained with the de-duped data relative to one trained with the full ILSVRC 2012 training set, but the accuracies of the truncated GoogLeNet baseline was unaffected. We saw a drop of 2% points in our best RNN model.

It is worth noting that when fine-tuning the visual core we did not use the Stanford Dogs training set, and since the parameters of the visual core are held fixed while training the RNN on Dogs, this means the powerful visual processing component in the RNN is not trained on the final task. We
Figure 4: Pre-training of the visual core (left) and inference within the RNN (right).

performed an experiment with a visual core fine-tuned on the Stanford Dogs training data, and we did not see an increase in performance, demonstrating again that the final RNN model is fairly robust to the pre-training and fine-tuning procedure.

3 EXPERIMENTAL RESULTS

We trained and evaluated our model on the Stanford Dogs fine-grained categorization data set (Khosla et al., 2011). The task is to categorize each of 8,580 test images as containing one of 120 dog breeds. The training set consists of 100 images per class, and the test images are unevenly distributed across classes, averaging about 71 test images per class. The training and test sets both include bounding boxes that provide a tight crop around the target dog, and while the best results we know of in the literature use the bounding boxes both in training and testing, we use neither the training nor testing boxes. We follow the practice common in the literature of augmenting the training set by reflecting the images along the vertical axis. Our model starts from the full images, without cropping, reshaping, or scaling. We performed experiments and chose hyperparameters using an 80/20 training/validation split of the Stanford Dogs training set. We selected hyperparameters (e.g. learning rate, sample variance) using the 20% validation set then trained on the full training set, and we only performed final evaluation on the Dogs test set on our selected hyperparameters.

The background in the images is not highly correlated with the class label, so any method not using the bounding boxes needs to localize the object of interest in order to classify it. This is a nice task to explore for our attention model in a couple ways: (1) the model can first leverage the context image in order to focus its glimpses on the object of interest, and (2) we can intuit which parts of the image the model should observe to make a prediction. With many other natural image object classification data sets, such as ImageNet, the signal from the surrounding context is mixed with the object for classification (e.g. boats are expected to be surrounded by water). The size of the data set is also more suitable to a deep learning method than most other available fine-grained data sets, though Caltech-UCSD Birds 2011 (Wah et al., 2011) is similar in size with 12,000 training images for 200 categories. Lastly, it remains a difficult data set, with a large amount of intra-class variation, similarity across classes, and large variation in pose, lighting, and background (Figure 1).

Table 1(a) shows the mean accuracy (mA) for different combinations of resolutions and number of glimpses. We experimented with high, medium, and low resolutions individually, medium and high combined, and all three resolutions and with one, two, and three glimpses. The table also shows previously published results on the data set. Versions of our model that use medium and low

1Missing from the results are entries to the FGComp 2013 fine-grained competition. There are high-performing entries from deep learning models in the dogs category, though to our knowledge these models have not been published. CognitiveVision and CafeNet scored 61% and 57% on the challenge, respectively, using training and test bounding boxes. The challenge training set is from Stanford Dogs, but the test set is independent, the class labels have not been made public, and the evaluation server is no longer running. As such, we cannot compare directly to these numbers, but we have been told anecdotally that scores on the FGComp 2013 challenge tend to be about 10% absolute lower than on the Stanford Dogs test set.
Table 1: Results on Stanford Dogs for (a) our RNN model and (b) GoogLeNet and previous state-of-the-art results, measured by mean accuracy (mA) as described in Chai et al. (2013). The GoogLeNet models were pre-trained on the de-duped ILSVRC 2012 training set and fine-tuned with the Stanford Dogs training set. Results marked with a star indicate use of tight ground truth bounding boxes around the dogs in training and testing.

| # glimpses     | 1  | 2  | 3  | (a)          | (b)          |
|----------------|----|----|----|--------------|--------------|
| high res only  | 0.43 | 0.50 | 0.51 | Yang et al. (2012)* 0.38 |               |
| medium res only| 0.64 | 0.66 | 0.66 | Chai et al. (2013)* 0.46 |               |
| low res only   | 0.55 | 0.55 | 0.56 | Gavves et al. (2013)* 0.50 |               |
| high+medium res| 0.64 | 0.67 | 0.67 | GoogLeNet 96×96 0.42 |               |
| 3-resolution   | 0.68 | 0.69 | 0.68 | GoogLeNet 224×224 0.75 |               |

resolution patches outperform state-of-the-art results. When using only two small high-resolution patches from the image, our model matches the best published result. All previously published results shown use ground truth bounding boxes for training and testing while our model does not.
Figure 5: Examples for the high-resolution model with 1 glimpse only: the system takes the original image (left), subsamples it into the context image (center) used to predict a single high resolution glimpse (right). Lines surrounded by green were correctly classified, while red indicates a classification error. Note that while the bottom example is misclassified because of the limitation to a very narrow window, the model still learned to look at the most informative location, the dog face and did not confuse it with a human face.

While the high-resolution single-glimpse model has the lowest performance of the set, visualizations of the selected glimpse locations show that it is learning to take a good first action (Figure 5). These are fairly representative of the behavior of the model, which most frequently chooses a patch on or near the dog’s face. While it may make an informative first glimpse, it is often not able to correctly classify the dog from that single sample. It is important to note that the model automatically learned to focus on the most discriminative features such as faces and fur without ever receiving spatial clues such as bounding boxes. This is pretty remarkable in that bounding boxes are usually required for computer vision tasks such as object detection, and obtaining bounding boxes at scale is difficult and expensive. While we are not exploring the detection task here, the model learned some form of detection without the help of bounding boxes, this approach could help alleviate the lack of supervised data. The figure shows two images where it classified the dog correctly in green, and one in red where it assigned an incorrect label. One pathological pattern we noticed is that if there are two dogs in the image, it often chooses a patch that is halfway between the two. A set of randomly chosen examples is shown in the appendix with Figure 6.

Comparison to results not using deep learning does not give a good sense of the strength of the model, however. In the last couple years deep nets have been winning the ILSVRC classification challenge by a significant margin, so it may be expected that a deep neural net would outperform the existing results. To address this we experimented with the GoogLeNet model on the full image...
without the attention RNN. We experimented with two baseline versions of GoogLeNet: the “full” model from [Szegedy et al. (2014a)], trained and tested on 224×224 padded versions of the full Dog images; and the “truncated” model that has the same layers as our attention visual core but takes 96×96 padded full Dog images in place of the glimpse input. Both versions were pre-trained using the de-duped ILSVRC 2012 data set, then the top fully-connected layer and softmax layers were resized and reinitialized, and the full model was trained to convergence on the Dogs training set. In addition to the mirroring applied for RNN training, brightness and color transformations were also applied to the training images. The full GoogLeNet baseline reached 75% mA on the Dogs test set, which is a 16% point increase over our three-resolution, two-glimpse attention model. The truncated baseline, however, only achieved 42% mA, demonstrating that the lost resolution and reduced network size has a large effect. To better compare to the 42% result, we trained a version of the attention model that uses one glimpse and only the medium resolution, rescaled to 96×96, and this model reached 64% mA. This version has the same number of input pixels available for classification as the truncated baseline and performs about the same amount of processing on those pixels, but displays a significant increase over the truncated baseline, which we attribute to it choosing a more informative patch to process based on the context image. If we use one glimpse and all three resolutions for glimpse input, mean accuracy increases to 68%.

Lastly, it is interesting to compare one-, two-, and three-glimpse versions of the three-resolution model. As reported above, the one-glimpse three-resolution model reaches 68% mA. We expected to see significant benefit from more glimpses, but the two- and three-glimpse models reached 69% and 68%, respectively, after training error converged. One likely cause is that the three-resolution glimpse contains a lot of information about the full image, so the gain from additional glimpses is reduced. Compare this with the improvement for additional glimpses when using just the high-resolution glimpse: 43% for one glimpse and 50% for two glimpses. However, even using only the high resolution, using three glimpses only increases the accuracy to 51%. Another factor may be that the RNN is not passing enough of the information from the first glimpse along to the classification layer. It is future work to explore using LSTM cells and increasing the recurrent capacity of the network.

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Note that our GoogLeNet baselines are using only one view of the whole image and a single model for a more meaningful comparison to our single view and single model attention system. Results can be improved substantially by using standard techniques such as multi-view aggregations and model ensembles.
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A RANDOM VALIDATION SAMPLES
Under review as a workshop contribution at ICLR 2015
Figure 6: 10 random validation samples from different systems: from left to right, the system using all 3 resolutions (high, medium and low) and 3 glimpses, the system with 3 resolutions but just 1 glimpse, the system with high resolution only, with 3 and 1 glimpses. For each system, we show the original image on the left and the composite image on the right, which is the superposition of all glimpses. Green borders around images indicate a correct classification, while red borders indicate an error. The leftmost column is the most accurate system, however it is interesting to see that while the rightmost column is least accurate, the model correctly directs its attention to the most informative areas (dog faces) and usually simply lacks enough information to correctly indentify the class. It is also interesting to note in the last sample, the rightmost model correctly classifies a breed given a non-face feature, showing that the system has learned to identify useful parts on its own and does not rely solely of facial features.