DATA-DEPENDENT INITIALIZATIONS OF CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT
Convolutional Neural Networks spread through computer vision like a wildfire, impacting almost all visual tasks imaginable. Despite this, few researchers dare to train their models from scratch. Most work builds on one of a handful of ImageNet pre-trained models, and fine-tunes or adapts these for specific tasks. This is in large part due to the difficulty of properly initializing these networks from scratch. A small miscalibration of the initial weights leads to vanishing or exploding gradients, as well as poor convergence properties. In this work we present a fast and simple data-dependent initialization procedure, that sets the weights of a network such that all units in the network train at roughly the same rate, avoiding vanishing or exploding gradients. Our initialization matches the current state-of-the-art unsupervised or self-supervised pre-training methods on standard computer vision tasks, such as image classification and object detection, while reducing the pre-training time by three orders of magnitude. When combined with pre-training methods, our initialization significantly outperforms prior work, narrowing the gap between supervised and unsupervised pre-training.

1 INTRODUCTION
In recent years, Convolutional Neural Networks (CNNs) have improved performance across a wide variety of computer vision tasks (Szegedy et al., 2015; Simonyan & Zisserman, 2015; Girshick, 2015). Much of this improvement stems from the ability of CNNs to use large datasets better than previous methods. In fact, good performance seems to require large datasets: the best-performing methods usually begin by “pre-training” CNNs to solve the million-image ImageNet classification challenge (Russakovsky et al., 2015). This “pre-trained” representation is then “fine-tuned” on a smaller dataset where the target labels may be more expensive to obtain. These fine-tuning datasets generally do not fully constrain the CNN learning: different initializations can be trained until they achieve equally high training-set performance, but they will often perform very differently at test time. For example, initialization via ImageNet pre-training is known to produce a better-performing network at test time across many problems. However, little else is known about which other factors affect a CNN’s generalization performance when trained on small datasets. There is a pressing need to understand these factors, first because we can potentially exploit them to improve performance on tasks where few labels are available. Second they may already be confounding our attempts to evaluate pre-training methods. A pre-trained network which extracts useful semantic information but cannot be fine-tuned for spurious reasons can be easily overlooked. Hence, this work aims to explore how to better fine-tune CNNs. We show that simple statistical properties of the network, which can be easily measured using training data, can have a significant impact on test time performance. Surprisingly, we show that controlling for these statistical properties leads to a fast and general way to improve performance when training on relatively little data.

Empirical evaluations have found that when transferring deep features across tasks, freezing weights of some layers during fine-tuning generally harms performance (Yosinski et al., 2014). These results suggest that, given a small dataset, it is better to adjust all of the layers a little rather than to adjust just a few layers a large amount, and so perhaps the ideal setting will adjust all of the layers the

Code available: https://github.com/philkr/magic_init
same amount. While these studies did indeed set the learning rate to be the same for all layers, somewhat counterintuitively this does not actually enforce that all layers learn at the same rate. To see this, say we have a network where there are two convolution layers separated by a ReLU. Multiplying the weights and bias term of the first layer by a scalar $\alpha > 0$, and then dividing the weights (but not bias) of the next (higher) layer by the same constant $\alpha$ will result in a network which computes exactly the same function. However, note that the gradients of the two layers are not the same: they will be divided by $\alpha$ for the first layer, and multiplied by $\alpha$ for the second. Worse, an update of a given magnitude will have a smaller effect on the lower layer than the higher layer, simply because the lower layer’s norm is now larger. Using this kind of reparameterization, it is easy to make the gradients for certain layers vanish during fine-tuning, or even to make them explode, resulting in a network that is impossible to fine-tune despite representing exactly the same function. Conversely, this sort of re-parameterization gives us a tool we can use to calibrate layer-by-layer learning to improve fine-tuning performance, provided we have an appropriate principle for making such adjustments.

Where can we look to find such a principle? A number of works have already suggested that statistical properties of network activations can impact network performance. Many focus on initializations which control the variance of network activations. Krizhevsky et al. (2012) carefully designed their architecture to ensure gradients neither vanish nor explode. However, this is no longer possible for deeper architectures such as VGG (Simonyan & Zisserman, 2015) or GoogLeNet (Szegedy et al., 2015). Glorot & Bengio (2010); Saxe et al. (2013); Sussillo & Abbot (2015); He et al. (2015); Bradley (2010) show that properly scaled random initialization can deal with the vanishing gradient problem, if the architectures are limited to linear transformations, followed by a very specific non-linearities. Saxe et al. (2013) focus on linear networks, Glorot & Bengio (2010) derive an initialization for networks with tanh non-linearities, while He et al. (2015) focus on the more commonly used ReLUs. However, none of the above papers consider more general network including pooling, dropout, LRN layers (Krizhevsky et al., 2012), or DAG-structured networks (Szegedy et al., 2015). We argue that initializing the network with real training data improves these approximations and achieves a better performance. Early approaches to data-driven initializations showed that whitening the activations at all layers can mitigate the vanishing gradient problem (LeCun et al., 1998), but it does not ensure all layers train at an equal rate. More recently, batch normalization (Ioffe & Szegedy, 2015) enforces that the output of each convolution and fully-connected layer are zero mean with unit variance for every batch. In practice, however, this means that the network’s behavior on a single example depends on the other members of the batch, and removing this dependency at test-time relies on approximating batch statistics. The fact that these methods show improved convergence speed at training time suggests we are justified in investigating the statistics of activations. However, the main goal of our work differs in two important respects. First, these previous works pay relatively little attention to the behavior on smaller training sets, instead focusing on training speed. Second, while all above initializations require a random initialization, our approach aims to handle structured initialization, and even improve pre-trained networks.

2 Preliminaries

We are interested in parameterizing (and re-parameterizing) CNNs, where the output is a highly non-convex function of both the inputs and the parameters. Hence, we begin with some notation which will let us describe how a CNN’s behavior will change as we alter the parameters. We focus on feed-forward networks of the form

$$z_k = f_k(z_{k-1}; \theta_k),$$

where $z_k$ is a vector of hidden activations of the network, and $f_k$ is a transformation with parameters $\theta_k$. $f_k$ may be a linear transformation $f_k(z_k'; \theta_k) = W_k z_{k-1} + b_k$, or it may be a non-linearity $f_{k+1}(z_k; \theta_k) = \sigma_{k+1}(z_k')$ such as a rectified linear unit (ReLU) $\sigma(x) = \max(x, 0)$. Other common non-linearities include local response normalization or pooling (Krizhevsky et al., 2012; Szegedy et al., 2015; Simonyan & Zisserman, 2015). However, as is common in neural networks, we assume these nonlinearities are not parametrized and kept fixed during training. Hence, $\theta_k$ contains only $(W_k, b_k)$ for each affine layer $k$.

To deal with spatially-structured inputs like images, most hidden activations $z_k \in \mathbb{R}^{C_k \times A_k \times B_k}$ are arranged in a two dimensional grid of size $A_k \times B_k$ (for image width $A_k$ and height $B_k$) with $C_k$
channels per grid cell. We let \( z_0 \) denote the input image. The final output, however, is generally not spatial, and so later layers are reduced to the form \( z_N = \mathbb{R}^{C_N \times 1 \times 1} \), where \( C_N \) is the number of output units. The last of these outputs is converted into a loss with respect to some label; for classification, the approach is to convert the final output into a probability distribution over labels via a Softmax function. Learning aims to minimize the expected loss over the training dataset. Despite the non-convexity of this learning problem, backpropagation and Stochastic Gradient Descent often finds good local minima if initialized properly (LeCun et al., 1998).

Given an arbitrary neural network, we next aim for a good parameterization. A good parameterization should be able to learn all weights of a network equally well. We measure how well a certain weight in the network learns by how much the gradient of a loss function would change it. A large change means it learns more quickly, while a small change implies it learns more slowly. We initialize our network such that all weights in all layers learn equally fast.

3 Data-dependent initialization

Given an \( N \)-layer neural network with loss function \( \ell(z_N) \), we first define \( C_{k,i,j}^2 \) to be the expected norm of the gradient with respect to weights \( W_k(i,j) \) in layer \( k \):

\[
C_{k,i,j}^2 = \mathbb{E}_{z_0 \sim D} \left[ \left( \frac{\partial}{\partial W_k(i,j)} \ell(z_N) \right)^2 \right]
\]

(1)

where \( D \) is a set of input images and \( y_k \) is the backpropagated error. Similar reasoning can be applied to the biases \( b_k \), but where the activations are replaced by the constant 1. To not rely on any labels during initialization, we use a random linear loss function \( \ell(z_N) = \eta \cdot z_N \), where \( \eta \sim \mathcal{N}(0,I) \) is sampled from a unit Gaussian distribution. In other words, we initialize the top gradient to a random Gaussian noise vector \( \eta \) during backpropagation. We sample a different random loss \( \eta \) for each image.

In order for all parameters to learn at the same “rate,” we require the change in eq. 1 to be proportional to the magnitude of the weights \( \|W_k\|_2 \) of the current layer; i.e.,

\[
\bar{C}_{k,i,j} = \frac{C_{k,i,j}^2}{\|W_k\|_2^2}
\]

(2)

is constant for all weights. However this is hard to enforce, because for non-linear networks the backpropagated error \( y_k \) is a function of the activations \( z_{k-1} \). A change in weights that affects the activations \( z_{k-1} \) will indirectly change \( y_k \). This effect is often non-linear and hard to control or predict.

We thus simplify Equation (2): rather than enforce that the individual weights all learn at the same rate, we enforce that the columns of weight matrix \( W_k \) do so, i.e.:

\[
\bar{C}_{k,j} = \frac{1}{N} \sum_i \bar{C}_{k,i,j} = \frac{1}{N\|W_k\|_2^2} \mathbb{E}_{z_0 \sim D} \left[ z_{k-1}(j)^2 \|y_k\|_2^2 \right],
\]

(3)

should be approximately constant, where \( N \) is the number of rows of the weight matrix. As we will show in Section 4.1, all weights tend to train at roughly the same rate even though the objective does not enforce this. Looking at Equation (3), the relative change of a column of the weight matrix is a function of 1) the magnitude of a single activation of the bottom layer, and 2) the norm of the backpropagated gradient. The value of a single input to a layer will generally have a relatively small impact on the norm of the gradient to the entire layer. Hence, we assume \( z_{k-1}(j) \) and \( \|y_k\|_2 \) are independent, leading to the following simplification of the objective:

\[
\bar{C}_{k,j} \approx \mathbb{E}_{z_0 \sim D} \left[ z_{k-1}(j)^2 \right] \mathbb{E}_{y_k \sim D} \left[ \|y_k\|_2^2 \right] \frac{1}{N\|W_k\|_2^2},
\]

(4)

This approximation conveniently decouples the change rate per column, which depends on \( z_{k-1}(j)^2 \), from the global change rate per layer, which depends on the gradient magnitude \( \|y_k\|_2^2 \), allowing us to correct them in two separate steps.
present multiple data-driven weight initializations. We aim to ensure that each channel that a layer receives a similarly distributed input. It is straightforward to initialize weights in affine layers such that the units have outputs following similar distributions. E.g., we could enforce that layer $k$ activations $z_k(i, a, b)$ have $\mathbb{E}_{z_k \sim D, a, b} [z_k(i, a, b)] = \beta$ and $\mathbb{E}_{z_k \sim D, a, b} [(z_k(i, a, b) − \beta)^2] = 1$ simply via properly-scaled random projections, where $a$ and $b$ index over the 2D spatial extent of the feature map. However, we next have to contend with the nonlinearity $\sigma(\cdot)$. Thankfully, most nonlinearities (such as sigmoid or ReLU) operate independently on different channels. Hence, the different channels will undergo the same transformation, and the output channels will follow the same distribution if the input channels do (though the outputs will generally not be the same distribution as the inputs). In fact, most common CNN layers that apply a homogeneous operation to uniformly-sized windows of the input with regular stride, such as local response normalization, and pooling, empirically preserve this identical distribution requirement as well, making it broadly applicable.

We normalize the network activations using empirical estimates of activation statistics obtained from actual data samples $z_0 \sim D$. In particular, for each affine layer $k \in \{1, 2, \ldots, N\}$ in a topological ordering of the network graph, we compute the empirical mean and standard deviations for all outgoing activations and normalize the weights $W_k$ such that all activations have unit variance and mean $\beta$. This procedure is summarized in Algorithm 1.

The variance of our estimate of the sample statistics falls with the size of the sample $|D|$. In practice, for CNN initialization, we find that on the order of just dozens of samples is typically sufficient.

Note that this simple empirical initialization strategy guarantees affine layer activations with a particular center and scale while making no assumptions (beyond non-zero variance) about the inputs to the layer, making it robust to any exotic choice of non-linearity or other intermediate operation. This is in contrast with existing approaches designed for particular non-linearities and with architectural constraints. Extending these methods to handle operations for which they weren’t designed while maintaining the desired scaling properties may be possible, but it would at least require careful thought, while our simple empirical initialization strategy generalizes to any operations and DAG architecture with no additional implementation effort.

On the other hand, note that for architectures which are not purely feed-forward, the assumption of identically distributed affine layer inputs may not hold. GoogLeNet (Szegedy et al., 2015), for example, concatenates layers which are computed via different operations on the same input, and hence may not be identically distributed, before feeding the result into a convolution. Our method cannot guarantee identically distributed inputs for arbitrary DAG-structured networks, so it should be applied to non-feed-forward networks with care.

### Algorithm 1 Within-layer initialization.

```plaintext
for each affine layer $k$ do
    Initialize weights from a zero-mean Gaussian $W_k \sim \mathcal{N}(0, I)$ and biases $b_k = 0$
    Draw samples $z_0 \in \mathcal{D} \subset D$ and pass them through the first $k$ layers of the network
    Compute the per-channel sample mean $\hat{\mu}_k(i)$ and variance $\hat{\sigma}_k(i)^2$ of $z_k(i)$
    Rescale the weights by $W_k(i, :) \leftarrow W_k(i, :) / \hat{\sigma}_k(i)$
    Set the bias $b_k(i) \leftarrow \beta - \hat{\mu}_k(i) / \hat{\sigma}_k(i)$ to center activations around $\beta$
end for
```

In Section 3.1, we show how to satisfy $\mathbb{E}_{z_0 \sim D} [z_{k-1}(i)^2] = c_k$ for a layer-wise constant $c_k$. In Section 3.2, we then adjust this layer-wise constant $c_k$ to ensure that all gradients are properly calibrated between layers, in a way that can be applied to pre-initialized networks. Finally, in Section 3.3 we present multiple data-driven weight initializations.

### 3.1 Within-layer weight normalization

We aim to ensure that each channel that a layer $k + 1$ receives a similarly distributed input. It is straightforward to initialize weights in affine layers such that the units have outputs following similar distributions. E.g., we could enforce that layer $k$ activations $z_k(i, a, b)$ have $\mathbb{E}_{z_k \sim D, a, b} [z_k(i, a, b)] = \beta$ and $\mathbb{E}_{z_k \sim D, a, b} [(z_k(i, a, b) − \beta)^2] = 1$ simply via properly-scaled random projections, where $a$ and $b$ index over the 2D spatial extent of the feature map. However, we next have to contend with the nonlinearity $\sigma(\cdot)$. Thankfully, most nonlinearities (such as sigmoid or ReLU) operate independently on different channels. Hence, the different channels will undergo the same transformation, and the output channels will follow the same distribution if the input channels do (though the outputs will generally not be the same distribution as the inputs). In fact, most common CNN layers that apply a homogeneous operation to uniformly-sized windows of the input with regular stride, such as local response normalization, and pooling, empirically preserve this identical distribution requirement as well, making it broadly applicable.

We normalize the network activations using empirical estimates of activation statistics obtained from actual data samples $z_0 \sim D$. In particular, for each affine layer $k \in \{1, 2, \ldots, N\}$ in a topological ordering of the network graph, we compute the empirical mean and standard deviations for all outgoing activations and normalize the weights $W_k$ such that all activations have unit variance and mean $\beta$. This procedure is summarized in Algorithm 1.

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### 3.2 Between-layer scale adjustment

Because the initialization given in Section 3.1 results in activations $z_k(i)$ with unit variance, the expected change rate $C^2_{k, i}$ of a column $i$ of the weight matrix $W_k$ is constant across all columns $i$,
Algorithm 2 Between-layer normalization.

Draw samples \( z_0 \in \hat{D} \subset D \)

repeat

Compute the ratio \( \check{C}_k = E_j \left[ \check{C}_{k,j} \right] \)

Compute the average ratio \( \check{C} = \left( \prod_k C_k \right)^{1/N} \)

Compute a scale correction \( r_k = \left( \check{C} / \check{C}_k \right)^{\alpha/2} \) with a damping factor \( \alpha < 1 \)

Correct the weights and biases of layer \( k \): \( b_k \leftarrow r_k b_k, W_k \leftarrow r_k W_k \)

Undo the scaling \( r_k \) in the layer above

until Convergence (roughly 10 iterations)

under the approximation given in Equation (4). However, this does not provide any guarantee of the scaling of the change rates between layers.

We use an iterative procedure to obtain roughly constant parameter change rates \( C^2_{k,i} \) across all layers \( k \) (as well as all columns \( i \) within a layer), given previously-initialized weights. At each iteration we estimate the average change ratio \( (\check{C}_{k,i,j}) \) per layer. We also estimate a global change ratio, as the geometric mean of all layer-wise change ratios. The geometric mean ensures that the output remains unchanged in completely homogeneous networks. We then scale the parameters for each layer to be closer to this global change ratio. We simultaneously undo this scaling in the layer above, such that the function that the entire network computes is unchanged. This scaling can be undone by inserting an auxiliary scaling layer after each affine layer. However for homogeneous non-linearities, such as ReLU, Pooling or LRN, this scaling can be undone at in the next affine layer without the need of a special scaling layer. The between-layer scale adjustment procedure is summarized in Algorithm 2. Adjusting the scale of all layers simultaneously can lead to an oscillatory behavior. To prevent this we add a small damping factor \( \alpha \) (usually \( \alpha = 0.25 \)). With a relatively small number of steps (we use 10), this procedure results in roughly constant initial change rates of the parameters in all layers of the network, regardless of its depth.

3.3 Weight initializations

Until now, we used a random Gaussian initialization of the weights, but our procedure does not require this. Hence, we explored two data-driven initializations: a PCA-based initialization and a \( k \)-means based initialization. For the PCA-based initialization, we set the weights such that the layer outputs are white and decorrelated. For each layer \( k \) we record the features activations \( z_{k-1} \) of each channel \( c \) across all spatial locations for all images in \( D \). Then then use the first \( M \) principal components of those activations as our weight matrix \( W_k \). For the \( k \)-means based initialization, we follow Coates & Ng (2012) and apply spherical \( k \)-means on whitened feature activations. We use the cluster centers of \( k \)-means as initial weights for our layers, such that each output unit corresponds to one centroid of \( k \)-means. \( k \)-means usually does a better job than PCA, as it captures the modes of the input data, instead of merely decorrelating it. We use both \( k \)-means and PCA on just the convolutional layers of the architecture, as we don’t have enough data to estimate the required number of weights for fully connected layers.

In summary, we initialize weights or all filters (§ 3.3), then normalize those weights such that all activations are equally distributed (§ 3.1), and finally rescale each layer such that the gradient ratio is constant across layers (§ 3.2). This initialization ensures that all weights learn at approximately the same rate, leading to a better convergence and more accurate models, as we will show next.

4 Evaluation

We implement our initialization and all experiments in the open-source deep learning framework Caffe (Jia et al., 2014). To assess how easily a network can be fine-tuned with limited data, we use the classification and detection challenges in PASCAL VOC 2007 (Everingham et al., 2014), which contains 5011 images for training and 4952 for testing.
Architectures Most of our experiments are performed on the 8 layer CaffeNet architecture a small modification of AlexNet (Krizhevsky et al., 2012). We use the default architecture for all comparisons, except for Doersch et al. (2015) which removed groups in the convolutional layers. We also show results on the much deeper GoogLeNet (Szegedy et al., 2015) and VGG (Simonyan & Zisserman, 2015) architectures.

Image classification The VOC image classification task is to predict the presence or absence of each of 20 object classes in an image. For this task we fine-tune all networks using a sigmoid cross-entropy loss on random crops of each image. We optimize each network via Stochastic Gradient Descent (SGD) for 80,000 iterations with an initial learning rate of 0.001 (dropped by 0.5 every 10,000 iterations), batch size of 10, and momentum of 0.9. The total training takes one hour on a Titan X GPU for CaffeNet. We tried different settings for various methods, but found these setting to work best for all initializations. At test time we average 10 random crops of the image to determine the presence or absence of an object. The CNN estimates the likelihood that each object is present, which we use as a score to compute a precision-recall curve per class. We evaluate all algorithms using mean average precision (mAP) (Everingham et al., 2014).

Object detection In addition to predicting the presence of absence of an object in a scene, object detection requires the precise localization of each object using a bounding box. We again evaluate mean average precision (Everingham et al., 2014). We fine-tune all our models using Fast R-CNN (Girshick, 2015). For a fair comparison we varied the parameters of the fine-tuning for each of the different initializations. We tried three different learning rates (0.01, 0.002 and 0.001) dropped by 0.1 every 50,000 iterations, with a total of 150,000 training iterations. We used multi-scale training and fine-tuned all layers. All other settings were kept at their default values. Training and evaluation took roughly 8 hours in a Titan X GPU for CaffeNet. All models are trained from scratch unless otherwise stated.

For both experiments we use 160 images of the VOC2007 training set for our initialization. 160 images are sufficient to robustly estimate activation statistics, as each unit usually sees tens of thousands of activations throughout all spatial locations in an images. At the same time, this relatively small set of images keeps the computational cost low.

4.1 Scaling and Learning Algorithms

We begin our evaluation by measuring and comparing the relative change rate \( \tilde{C}_{k,i,j} \) of all weights in the network (see Equation (2)) for different initializations. We estimate \( \tilde{C}_{k,i,j} \) using 100 images of the VOC 2007 validation set. We compare our models to an ImageNet pretrained model, initialized with random Gaussian weights (with standard deviation \( \sigma = 0.01 \)), an unscaled \( k \)-means initialization, as well as the Gaussian initialization in Caffe (Jia et al., 2014), for which biases and standard deviations were handpicked per layer. Figure 1a visualizes the average change rate per layer. Our initialization, as well as the ImageNet pretrained model, have similar change rates for all layers (i.e., all layers learn at the same rate), while random initializations and \( k \)-means have a
drastically different change rates. Figure 1b measures the coefficient of variation of the change rate for each layer, defined as the standard deviation of the change rate, divided by their mean value. Our coefficient of variation is low throughout all layers, despite scaling the rate of change of columns of the weight matrix, instead of individual elements. Note that the low values are mirrored in the hand-tuned Caffe initialization.

Next we explore how those different initializations perform on the VOC 2007 classification task, as shown in Table 1. We train both a random Gaussian and k-means initialization using different initial scalings. Without scaling the random Gaussian initialization fares quite well, however the k-means initialization does poorly, due to the worse initial change rate as shown in Figure 1. Correcting for the within-layer scaling alone does not improve the performance much, as it worsens the between-layer scaling for both initializations. However in combination with the between-layer adjustment both initializations perform very well.

Both the between-layer and within-layer scaling could potentially be addressed by a stronger second order optimization method, such as ADAM (Kingma & Ba, 2015) or batch normalization (Ioffe & Szegedy, 2015). In general, ADAM is able to slightly improve on SGD for an unscaled initialization, especially when combined with batch normalization. Neither batch-norm nor ADAM alone or combined does perform as well as simple SGD with our k-means initialization. More interestingly, our initialization complements those stronger optimization methods and we see an improvement by combining them with our initialization.

4.2 WEIGHT INITIALIZATION

Next we compare our Gaussian, PCA and k-means based weights, with initializations proposed by Glorot & Bengio (2010) (commonly known as “xavier”), He et al. (2015), and a carefully chosen Gaussian initialization of Jia et al. (2014). We followed the suggestions of He et al. and used their initialization only for the convolutional layers, while choosing a random Gaussian initialization for the fully connected layers. We compare all methods on both classification and detection performance in Table 2.

The first thing to notice is that both Glorot & Bengio and He et al. perform worse than a carefully chosen random Gaussian initialization. One possibility for the drop in performance comes from the additional layers, such as Pooling or LRN used in CaffeNet. Neither Glorot & Bengio nor He et al. consider those layers but rather focus on linear layers followed by tanh or ReLU nonlinearities.

Our initialization on the other hand has no trouble with those additional layers and substantially improves on the random Gaussian initialization.

4.3 COMPARISON TO UNSUPERVISED PRE-TRAINING

We now compare our simple, properly scaled initializations to the state-of-the-art unsupervised pretraining methods on VOC 2007 classification and detection. Table 3 shows a summary of the results, including the amount of pre-training time, as well as the type of supervision used. Agrawal et al. (2015) uses egomotion, as measured by a moving car in a city to pre-train a model. While this information is not always readily available, it can be read from sensors and is thus “free.” We believe egomotion information does not often correlate with the kind of semantic information that is required for classification or detection, and hence the egomotion pretrained model performs worse than our random baseline. Wang & Gupta (2015) supervise their pre-training using relative motion

| Scaling       | SGD | SGD + BN | ADAM | ADAM + BN |
|---------------|-----|----------|------|-----------|
| no scaling    | 50.8% | 41.2% | 51.6% | 49.4% | 50.9% | 52.0% | 55.7% | 53.8% |
| Within-layer (Ours) | 47.6% | 41.2% | -    | -     | 53.2% | 53.1% |
| Between-layer (Ours) | 52.7% | 55.7% | -    | -     | 54.5% | 57.2% |
| Both (Ours)   | 53.3% | **56.6%** | 56.6% | **60.0%** | 53.1% | **56.9%** | 56.9% | **59.8%** |

Table 1: Classification performance of various initializations, training algorithms and with and without batch normalization (BN) on PASCAL VOC2007 for both random Gaussian (Gaus.) and k-means (k-mns.) initialized weights.
Table 2: Comparison of different initialization methods on PASCAL VOC2007 classification and detection.

| Method                      | Classification | Detection |
|-----------------------------|----------------|-----------|
| Xavier Glorot & Bengio (2010) | 51.1%          | 40.4%     |
| MSRA He et al. (2015)       | 43.3%          | 37.2%     |
| Random Gaussian (hand tuned) | 53.4%          | 41.3%     |
| Ours (Random Gaussian)      | 53.3%          | 43.4%     |
| Ours (PCA)                  | 52.8%          | 43.1%     |
| Ours (k-means)              | 56.6%          | 45.6%     |

Table 3: Comparison of classification and detection results on the PASCAL VOC2007 test set.

| Method                       | Supervision | Pretraining time | Classification | Detection |
|------------------------------|-------------|------------------|----------------|-----------|
| Agrawal et al. (2015)        | egomotion   | 10 hours         | 52.9%          | 41.8%     |
| Wang & Gupta (2015)          | motion      | 1 week           | 58.4%          | 44.0%     |
| Doersch et al. (2015)        | unsupervised | 4 weeks         | 55.3%          | 46.6%     |
| Krizhevsky et al. (2012)     | 1000 class labels | 3 days    | 78.2%          | 56.8%     |
| Ours (k-means)               | initialization | 54 seconds    | 56.6%          | 45.6%     |
| Ours + Agrawal et al. (2015) | egomotion   | 10 hours         | 54.2%          | 43.9%     |
| Ours + Wang & Gupta (2015)   | motion      | 1 week           | 58.1%          | 44.0%     |
| Ours + Doersch et al. (2015) | unsupervised | 4 weeks         | 65.3%          | 51.1%     |

4.4 DIFFERENT ARCHITECTURES

Finally we compare our initialization across different architectures, again using PASCAL 2007 classification and detection. We train both the deep architecture of Szegedy et al. (2015) and Simonyan & Zisserman (2015) using our k-means and Gaussian initializations. Unlike prior work we are able to train those models without any intermediate losses or stage-wise supervised pre-training. We simply add a sigmoid cross-entropy loss to the top of both networks. Unfortunately neither network outperformed CaffeNet in the classification tasks. GoogLeNet achieves a 50.0% and 55.0% mAP for
the two initializations respectively, while 16-layer VGG performs as 53.8% and 56.5%. This might have to do with the limited amount of supervised training data available to the model at during training. The training time was 4 and 12 times slower than CaffeNet, which made them prohibitively slow for detection.

4.5 IMAGENET TRAINING

Finally, we test our data-dependent initializations on two well-known CNN architectures which have been successfully applied to the ImageNet LSVRC 1000-way classification task: CaffeNet (Jia et al., 2014) and GoogLeNet (Szegedy et al., 2015). We initialize the 1000-way classification layers to 0 in these experiments (except in our reproductions of the reference models), as we find this improves the initial learning velocity.

CaffeNet  We train instances of CaffeNet using our initializations, with the architecture and all other hyperparameters set to those used to train the reference model: learning rate 0.01 (dropped by a factor of 0.1 every $10^5$ iterations), momentum 0.9, and batch size 256. We also train a variant of the architecture with no local response normalization (LRN) layers.

Our CaffeNet training results are presented in Figure 3. Over the first 100,000 iterations (Figure 3, middle row), and particularly over the first 10,000 (Figure 3, top row), our initializations reduce the network’s classification error on both the training and validation sets at a much faster rate than the reference initialization.

With the full 320,000 training iterations, all initializations achieve similar accuracy on the training and validation sets; however, in these experiments the carefully chosen reference initialization pulled non-trivially ahead of our initializations’ error after the second learning rate drop to a rate of $10^{-4}$. We do not yet know why this occurs, or whether the difference is significant.

Over the first 100,000 iterations, among models initialized using our method, the $k$-means initialization reduces the loss slightly faster than the random initialization. Interestingly, the model variant without LRN layers seems to learn just as quickly as the directly comparable network with LRNs, suggesting such normalizations may not be necessary given a well-chosen initialization.

GoogLeNet  We apply our best-performing initialization from the CaffeNet experiments—$k$-means—to a deeper network, GoogLeNet (Szegedy et al., 2015). We use the SGD hyperparameters from the Caffe (Jia et al., 2014) GoogLeNet implementation (specifically, the “quick” version which is trained for 2.4 million iterations), and also retrain our own instance of the model with the initialization used in the reference model (based on Glorot & Bengio (2010)).

Due to the depth of the architecture (22 layers, compared to CaffeNet’s 8) and the difficulty of propagating gradient signal to the early layers of the network, GoogLeNet includes additional “auxiliary classifiers” branching off from intermediate layers of the network to amplify the gradient signal to learn these early layers. To verify that networks initialized using our proposed method should have no problem backpropagating appropriately scaled gradients through all layers of arbitrarily deep networks, we also train a variant of GoogLeNet which omits the two intermediate loss towers, otherwise keeping the rest of the architecture fixed.

Our GoogLeNet training results are presented in Figure 4. We plot only the loss of the final classifier for comparability with the single-classifier model. The models initialized with our method learn much faster than the model using the reference initialization strategy. Furthermore, the model trained using only a single classifier learns at roughly the same rate as the original three loss tower architecture, and each iteration of training in the single classifier model is slightly faster due to the removal of layers to compute the additional losses. This result suggests that our initialization could significantly ease exploration of new, deeper CNN architectures, bypassing the need for architectural tweaks like the intermediate losses used to train GoogLeNet.

5 DISCUSSION

Our method is a conceptually simple data-dependent initialization strategy for CNNs which enforces empirically identically distributed activations locally (within a layer), and roughly uniform
Figure 2: Comparison of nearest neighbors for the given input image (top row) in the feature spaces of CaffeNet-based CNNs initialized using our method, the fully supervised CaffeNet, an untrained CaffeNet using Gaussian initialization, and three unsupervised or self-supervised methods from prior work. (For Doersch et al. (2015) we display neighbors in fc6 feature space; the rest use the fc7 features.) While our initialization is clearly missing the semantics of CaffeNet, it does preserve some non-specific texture and shape information, which is often enough for meaningful matches.

global scaling of weight gradients across all layers of arbitrarily deep networks. Our experiments (Section 4) demonstrate that this rescaling of weights results in substantially improved CNN representations for tasks with limited labeled data (as in the PASCAL VOC classification and detection training sets), improves representations learned by existing self-supervised and unsupervised methods, and substantially accelerates the early stages of CNN training on large-scale datasets (e.g., ImageNet). We hope that our initializations will facilitate further advancement in unsupervised and self-supervised learning as well as more efficient exploration of deeper and larger CNN architectures.

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Figure 3: Training and validation loss curves for the CaffeNet architecture trained for the ILSVRC-2012 classification task. The training error is unsmoothed in the topmost plot (10K); smoothed over one epoch in the others. The validation error is computed over the full validation set every 2000 iterations and is unsmoothed. Our initializations ($k$-means, Random) handily outperform both the carefully chosen reference initialization (Jia et al., 2014) and the MSRA initialization (He et al., 2015) over the first 100,000 iterations, but the other initializations catch up after the second learning rate drop at iteration 200,000.

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Figure 4: Training and validation loss curves for the GoogLeNet architecture trained for the ILSVRC-2012 classification task. The training error plot is again smoothed over roughly the length of an epoch; the validation error (computed every 4000 iterations) is unsmoothed. Note that our \( k \)-means initializations outperform the reference initialization, and the single loss model (lacking the auxiliary classifiers) learns at roughly the same rate as the model with auxiliary classifiers. The final top-5 validation error are 11.57\% for the reference model, 10.85\% for our single loss, and 10.69\% for our auxiliary loss model.

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