Pretraining boosts out-of-domain robustness for pose estimation

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Deep neural networks are highly effective tools for human and animal pose estimation. However, robustness to out-of-domain data remains a challenge. Here, we probe the transfer and generalization ability for pose estimation with two architecture classes (MobileNetV2s and ResNets) pretrained on ImageNet. We generated a novel dataset of 30 horses that allowed for both within-domain and out-of-domain (unseen horse) testing. We find that pretraining on ImageNet strongly improves out-of-domain performance. Moreover, we show that for both pretrained and networks trained from scratch, better ImageNet-performing architectures perform better for pose estimation, with a substantial improvement on out-of-domain data when pretrained. Collectively, our results demonstrate that transfer learning is particularly beneficial for out-of-domain robustness.

Pose estimation is an important tool for understanding behavior, as it belies analysis of movement kinematics, action recognition, and ethology [1–4]. Pose estimation on humans has reached remarkable capabilities due to innovations in both algorithms [5–11] and large-scale datasets [12–14]. However, it is a challenging problem due to small joints, occlusions, clothing, and changes in background and scene statistics. Thus, many networks suffer when applied to out-of-domain data, i.e. images that are sufficiently different from the training set. For instance, they fail on very articulated human movements like skiing, or other ‘rare poses’, if not in the training set [15, 16]. Moreover, animal pose estimation has additional challenges. Not all animals share the same keypoints, therefore a universal “animal pose detector” is not feasible. Even building animal-specific networks would require a lot of data, due to the large variability in body shapes, colors, and the number of species as well as breeds of a type of animal. Therefore, the question of how one can robustly learn from limited annotated datasets is of particular importance, and animal pose estimation datasets allow for generalization to be systematically tested [17].

How can robustness be achieved? Transfer learning, or the transferability of pretrained features from one task to another, is a powerful approach that has been well studied in computer vision [18–22]. It has been shown to improve performance on some human pose estimation tasks [5, 9, 23, 24], yet is not universally used in the top-performing networks on the human 2D/3D pose estimation benchmarks [25]. For keypoint detection, He et al. recently showed that pretraining on ImageNet did not result in overall performance improvements if randomly initialized models were allowed to train for much longer than usual, therefore suggesting that (given enough task-data) the main benefit of transfer learning is shorter training time, rather than performance [22]. However, it has not been tested whether pretraining on ImageNet offers advantages in robustness, for instance as measured by any performance advantage on out-of-domain data.

We address this by building a new pose estimation task of 8,114 labeled video frames from 30 Thoroughbred horses. We focus on horses as their diversity readily allows us to assess out-of-domain generalization, i.e. the ability to generalize to the different, unseen horses in different contexts. We created a task, called Horse-10, that uses only 10 horses for the test/train splits, and uses the other 20 horses to test out-of-domain performance (Figure 1). The data will be made available at deeplabcut.org.

Here we report two key insights: (1) higher ImageNet performance leads to better generalization for both within domain and on out-of-domain data for pose estimation but with a stronger effect on out-of-domain data (see Figure 2B). Thus, while it has been previously shown that training from scratch can match performance on in-domain data for sufficiently large amount of training data and training times [22], we show it clearly cannot match performance of pretrained networks on out-of-domain data (see Figure 5); (2) transfer learning improves robustness again most strongly for out-of-domain data, and yields up to 3 times more accurate results than training from scratch (see Figure 4D,E). Collectively, this sheds a new light on the inductive biases of “better ImageNet architectures” for visual tasks to be particularly beneficial for robustness, even beyond within domain data accuracy, on out-of-domain datasets.
FIG. 1. Horse Dataset: Example frames for each young Thoroughbred horse in the dataset. In each video the horse walks from left to right. The videos vary in horse color, the appearance of sunlight and shadow, and relative horse size as well as background. This makes the data set ideal for tests in robustness and generalization. To illustrate the horse-10 task we arranged the horses according to one split: the ten leftmost horses were used for train/test within-domain, and the rest are the out-of-domain held out horses.

Results

To test within and out-of-domain performance we created a new dataset of 30 different walking horses (Thoroughbreds that are led by different humans), resulting in a dataset of 8,114 images with 22 labeled body parts each. Horses have various coat colors and the “in-the-wild” aspect of the collected data at various Thoroughbred yearling sales and farms added additional complexity. The sunlight variation between each video added to the complexity of the learning challenge, as well as the handlers often wearing horse-leg-colored clothing. Some horses were in direct sunlight while others had the light behind them, and others were walking into and out of shadows, which was particularly problematic with a dataset dominated by dark colored coats (Figure 1). Thus, this dataset is ideal for testing robustness and out-of-sample generalization.

ImageNet accuracy predicts animal pose estimation accuracy

To probe the role of different ImageNet pretrained architectures, we compared four variants of MobileNetV2 with varying expansion ratios, as the width multiplier parameterizes ImageNet performance over a wide range (see Methods), and two variants of ResNets (50 and 101 layers deep). We utilized a ‘simple’ yet competitive pose estimation architecture [26, 27] embedded in DeepLabCut, a toolbox for data-set generation, training, and evaluation (see Methods). The architectures then consisted of either MobileNetV2s [28] or ResNets [29], where a single deconvolution layer is connected to the final convolutional layer to predict poses via body-part specific scoremaps as well as location refinement maps [26, 27]. We created 3 splits containing 10 random horses each, and then varied the amount of training data from these 10 horses (referred to as Horse-10, see Methods). As the horses could vary dramatically in size across frames, due to the “in-the-wild” variation in distance from the camera, we used a normalized pixel error; i.e. we normalized the raw pixel errors by the eye-to-nose distance and report the fraction within this distance (Figure 2A). In total, we found that all pretrained-ImageNet networks showed great performance on Horse-10 within domain (Figure 2B, S1).

To further assess the errors we computed the percent correct keypoints (PCK; defined as within 30% of the distance from nose-to-eye, see Methods) and found that performance was nearly 97% for ResNets (with at least 20% training data) and only fell to ≈ 93% on MobileNetV2-based models (Figure S2A). Even with very small datasets (5%, i.e. around 160 training images) performance was 80% to 85% on MobileNetV2 and ResNets, respectively (Figure S2A).

Next, we directly compare the ImageNet performance to their respective performance on this pose estimation task. We find Top-1% accuracy on ImageNet, corre-
FIG. 2. Transfer Learning boosts performance, especially on out-of-domain data. A: Illustration of the normalized error metric. B: Normalized Error vs. Network performance as ranked by the Top 1% accuracy on ImageNet (order by increasing ImageNet performance: MobileNetV2-0.35, MobileNetV2-0.5, MobileNetV2-0.75, MobileNetV2-1, ResNet-50, ResNet-101). The pose estimation performance is for 50% training set fraction. The faint lines indicate data for the three splits. LEFT: Test data is in red, train is blue. RIGHT: additionally, pink is out-of-domain data; dashed lines indicate networks trained from scratch. Better ImageNet networks perform better on Horse-10; this relationship is even stronger for out-of-domain data. C: Example frames with human annotated body parts vs. predicted body parts for MobileNetV2-0.35 and ResNet-50 architectures with ImageNet pretraining on out-of-domain horses. D: Normalized Error vs. Training Set Fraction of Horse-10. For reference, 5% training data is ≈ 160 frames. Darker to light red shades are test results for pretrained networks on within-domain data. Shades of pink show the test on out-of-domain data (order according to ImageNet performance: ResNet-101, ResNet-50, MobileNetV2-1, MobileNetV2-0.75, MobileNetV2-0.5, MobileNetV2-0.35). E: Same as C but for training from scratch. F: Same as D but for training from scratch. All lines are averages of 3 splits (see Methods).

lates with pose estimation error (linear fit: slope −0.33%, \( R^2 = 0.95, p = 0.001 \); Figures 2B). This linear relationship is consistent with a recently reported correlation of ImageNet accuracy and performance for various object recognition tasks [30].

Using pretrained-ImageNet networks significantly boosts out-of-domain performance

The larger challenge is posed by the out-of-domain horses, rather than on different frames for same horses as
used for training. Thus, we evaluated the performance of the networks that had been trained for various fractions of the training data and found that both MobileNetV2s and ResNets were robust (Figures 2B-D).

Most strikingly, on out-of-domain horses, the relationship between ImageNet performance and performance on Horse-10 was even stronger. This can be quantified by comparing the linear regression slope for out-of-domain test data: $-1.6\%$ pose-estimation improvement per percentage point of ImageNet performance, $R^2 = 0.95$, $p = 0.0008$ vs. within-domain test data $-0.33\%$, $R^2 = 0.95$, $p = 0.0010$ (Figures 2B-F). In other words, less powerful models (MobileNetV2s) seem to overfit more on the training data. We mused that this improved generalization could be a consequence of the ImageNet pretraining or the architectures themselves. Thus, we trained the different architectures only on the task itself.

**Task-based training from scratch**

To assess the impact of ImageNet pretraining we also trained all architectures from scratch. Thereby we could directly test if the increased slope for out-of-domain performance across networks was merely a result of more powerful network architectures.

When training from scratch directly on the task for the same amount of iterations (see Methods), we found that all networks performed well on within-domain data, given enough training data. The ResNets once again showed an advantage over the MobileNetV2 variants. All the networks performed worse on within domain compared to pretrained-ImageNet networks, and strikingly 2X worse on out-of-domain data (Figures 2E,F).

The PCK for all networks as a fraction of the training set size also reflected this decrease in performance compared to pretraining (Figures S2A-C). For example, while PCK with pretrained ResNet network was nearly 97% (with 20% of the training data), without pretraining this falls to around 80%. Out-of-domain performance drops substantially (pretrained vs. randomized initial weights; comparing Figure S2B to Figure S2C).

Without pretraining we find that the Top-1% accuracy on ImageNet ranking of models only weakly correlates with pose estimation error (linear fit: slope $-0.26\%$, $R^2 = 0.53$, $p = 0.166$; Figures 2B and S3B). On out-of-domain horses the slope was similar (slope $-0.21\%$, $R^2 = 0.54$, $p = 0.098$), unlike when training from pretrained checkpoints. Taken together, our results suggest that ImageNet pretraining significantly boosts generalization (vs. just being a feature of the architectures themselves).

Next we quantified the amount of performance gain across all networks (with vs. without pretraining). We found an up to 2X gain in performance (increase in PCK) with transfer learning (Figure 3A-C). Remarkably, for both ResNets and MobileNetV2s, pretraining on ImageNet boosts within domain and out-of-domain reduction in pixel-errors (Figure 4A,B), with the largest gains on out-of-domain data - with 90% of the training data there was a gain of up to a 3X (Figure 4B).

**From scratch networks cannot match the performance of pretrained-ImageNet networks on out-of-domain data**

He et al. recently showed that training ResNets directly on COCO data for object detection, instance segmentation and key point detection, catches-up with pretrained network accuracy when training for 6X more iterations as typical training schedules [22]. However, due to the nature of the task, they did not test this rela-
FIG. 4. Up to a 3X gain with transfer learning on out-of-domain data. A: Transfer learning gain vs. architectures with 50% of the data used for training (comparing pretrained networks to from-scratch from Figure 2B). B: Same as in A, but for varying levels of input data (5 to 90%), light to dark, respectively. All lines are averages of 3 splits.

Discussion

Here we report two key findings: (1) pretrained-ImageNet networks offer an advantage: shorter training times, less data requirements, and robustness on out-of-domain data, and (2) networks that have higher ImageNet performance lead to better generalization, especially on out-of-domain data. Recently, it was shown that for many object recognition datasets the transfer ability is improved when fine-tuning architectures with better ImageNet performance [21, 30]. In fact, Kornblith et al. find high correlation between between ImageNet and transfer accuracy for other recognition tasks \(r > 0.95\) [30]. In contrast to the exhaustive study by Kornblith et al., we only focused on two architecture types: ResNets [29] and MobileNetV2s [28]. However, we vary parameters of those networks to also span a broad range of ImageNet accuracies. Consistent with Kornblith et al, we find that ImageNet accuracy is weakly correlated with performance on pose estimation when trained from scratch \(R^2 = 0.53\), and strongly when fine-tuning \(R^2 = 0.95\). We also find that “better” ImageNet networks transfer better. Moreover, we show that transfer learning significantly improves performance on out-of-domain data.

Transfer learning

We show that for both within and out-of-domain pose estimation tasks, transfer learning improves performance. Most notably, transfer learning boosts out-of-domain generalization, improving up to 3X compared to networks without pretraining, and even when training for much longer (as suggested in [22]), this gap cannot be closed.

Another important insight is that for small amounts of data, pretrained networks offer a large advantage (Figures 4 & 5), which was the original motivation for DeepLabCut [27]. Corroborating He et al. we find that given enough training data, training from scratch, with purely task-driven training can match the performance of of transfer learning [22]; however, we also found that for out-of-domain data, pretraining helps significantly, boosting performance up to 3 times (Figure 4).

On the importance of data

Looking forward, this suggests that collecting annotations of task data (instead of pretraining data) is more useful. We think that benchmarks with different contexts, like Horse-10, are important to improve pose estimation algorithms for biological applications (i.e. for
small-scale lab-based experiments). A future goal will be to limit, or remove, training altogether. However, in order to create networks that generalize across laboratories and setups, transfer learning will be important for robustness. Yet, more work needs to be done to close the gap between within domain and out-of-domain generalization.

What is the limit of transfer learning? Would ever larger data sets give better generalization? Interestingly, it appears to strongly depend on what task the network was pretrained on. Recent work by Mahajan et al. showed that pretraining for large-scale hashtag predictions on Instagram data (3.5 billion images) improves classification, while at the same time possibly harming localization performance for tasks like object detection, instance segmentation, and keypoint detection [31]. This highlights the importance of the task, rather then the sheer size as a crucial factor. Further corroborating this insight, Li et al. showed that pretraining on large-scale object detection task can improve performance for tasks that require fine, spatial information like segmentation [32]. Thus, one interesting future direction to boost robustness could be to utilize networks pretrained on OpenImages, which contains bounding boxes for 15 million instances and close to 2 million images [33].

**MobileNetV2-DeepLabCut for fast pose estimation**

DeepLabCut is a flexible toolbox for pose estimation that uses pretrained-ImageNet models and requires minimal training data for accurate performance [27, 34, 35]. Here, we introduce new DeepLabCut variants that can achieve high accuracy but with 2.5X the speed as the ResNet backbone (Figure S4), making pretrained-MobileNetV2 an excellent option for real-time applications in the wild (on mobile-phones) and in the laboratory. If an end-user utilizes small training sets, ResNets offer an advantage, yet MobileNetV2s are significantly faster (Figure S4) and performs reasonably well, within domain; i.e. to match the ResNet-101 performance with 10% of the training set one needs about 50% for the best MobileNetV2. Potentially, the few pixels lost in accuracy is worth the significant speed improvement (twice as fast) for high-throughput experiments and for real-time applications. MobileNetV2 can run batch inference of (> 2,500 FPS) on a GPU. Using MobileNetV2 also has other advantages: one, MobileNetV2 has low memory demands, and even runs on mobile phones, as the name suggests; two: on CPUs one gets even more speed improvements (Figure S4).

What are the trade-offs? With more data for training the MobileNetV2 match the performance of ResNets trained with less labeling data (Figure 2B). However, the ResNets still perform best with matched amounts of data. Thus, to close this gap “Student-Teacher networks” could be used. For example, one could build a larger and more robust ResNet-101 network, then run inference to generate a larger dataset to train the MobileNetV2 variant for fast inference on within domain data.

**Conclusions**

We found a significant advantage of using pretrained networks for out-of-domain robustness. While there is still a gap to close, we believe this work demonstrates that transfer learning approaches are powerful to build robust architectures. We also demonstrate that ImageNet performance correlates with animal pose estimation accuracy on a challenging “in-the-wild” new horse.
FIG. 6. Summary of Findings: We present a new horse dataset for testing within and out-of-domain performance for pose estimation. We tested two classes of models, MobileNetV2s and ResNets, which span a wide range of performance on ImageNet. We find that networks that perform better on ImageNet are better for pose estimation. We also find that pretrained-ImageNet models strongly improve out-of-domain robustness.

dataset (Figure 6). Moreover, we add a new variant of networks to the open-source DeepLabCut package, MobileNetV2s, that pave the way for fast and accurate pose estimation. Collectively, our work highlights that pretrained networks require less training data, and allow for faster training, and boost robustness, especially for out-of-domain data.

Methods

Horse Dataset

Here we developed a novel horse data set comprising 30 different horses captured for 4 – 10 seconds with a GoPro camera (Resolution: 1920 × 1080, Frame Rate: 60 FPS), which we call Horse-30. We will make this dataset publicly available at deeplabcut.org. We used the DeepLabCut2.0 toolbox [35] for labeling. In the past DeepLabCut was benchmarked with various data sets: odor-guided navigation and reaching in mice, egg-laying in fruit flies [27], locomotion studies in mice [34], as well as hunting cheetahs [35]. We used the Horse dataset for benchmarking here. We downsampled the frames by a factor of 15% to speed-up the benchmarking process (288 × 162 pixels; one video was downsampled to 30%).

Using previously established anatomical landmarks for equine biomechanical evaluation [36, 37], the following 22 body parts were labeled by an expert in Thoroughbred horses (BR) across 8,114 frames: Nose, Eye, Nearknee, Nearestfootlock, Nearestfrontfoot, Offknee, Offfrontfoot, Offfrontfoot, Shoulder, Midshoulder, Elbow, Girth, Wither, Nearesthindlock, Nearesthindfetlock, Nearesthindfoot, Hip, Stifle, Offhindlock, Offhindfetlock, Offhindfoot, Ischium.

We created 3 splits that contain 10 randomly selected training horses each (referred to as Horse-10). For each training set we took a subset of 5% (∼ 160 frames), 10% (∼ 300 frames), 20% (∼ 560 frames), 50% (∼ 1470 frames), and 90% (∼ 2580 frames) of the frames for training, and then evaluated the performance on the training, test, and unseen (“out-of-domain”) horses (i.e. the other horses that were not in the given split of Horse-10). As metric we used mean average Euclidean error, which is computed by comparing the inferred poses for each body parts against the human prediction [35] as well as percent correct key-point (PCK) values; i.e. what fraction of machine-applied points fall within a specific range of human-labeled ground-truth labels; although we use a matching threshold of 30% of the head segment length (nose to eye for horse, which was computed by taking the median for all annotated images per horse) rather than 50% as for MPII pose [13].

DeepLabCut variants

For this study we utilized a recently introduced an animal pose estimation toolbox called DeepLabCut [27, 34, 35]. The TensorFlow [38]-based network architectures could be easily exchanged while keeping data loading, training, and evaluation consistent.

DeepLabCut [27, 35] is built on a subset of the deep feature detectors in DeeperCut [26], hence its name. The feature detectors in DeepLabCut consist of residual networks (ResNets) [29] followed by deconvolutional layers to predict pose scoremaps and location refinement maps, which can then be used for predicting the pose while also proving a confidence score [26, 27]. By default, we utilize an output stride of 16 for the ResNets (achieved by atrous convolution) and then upsample the filter banks with deconvolutions by a factor of two to predict the heatmaps and location-refinement at 1/8th of the original image size scale. This gives a good balance of feature-map size and accuracy. However, the ratio can, of course, be changed and this affects speed, while still being relatively robust [26].
Here we also introduce a new variant of DeepLabCut with the MobileNetV2 architecture [28] in addition to ResNets. MobileNetV2 utilizes depth-wise separable convolutions, inverted residual bottlenecks to significantly decrease the number of operations and memory needed while retaining high accuracy for ImageNet, object detection and image segmentation accuracy [28]. We configured the output-stride as 16 (by changing the (otherwise) last stride 2 convolution to stride 1). We utilized four variants of MobileNetV2 with different expansion ratios (0.35, 0.5, 0.75 and 1) as this ratio modulates the ImageNet accuracy from 60.3% to 71.8%, and pretrained models on ImageNet are available from TensorFlow [38]. The MobileNet-DeepLabCut version will be available in the DeepLabCut toolbox starting with version 2.1 and can easily be selected by changing the “net_type” variable. See the GitHub repository https://github.com/AlexEMG/DeepLabCut for details.

Training parameters

Most DeepLabCut parameters used here are consistent with the ones in DeepLabCut-2.0 [35]. The training loss is defined as the cross entropy loss for the scoremaps with the ones in DeepLabCut-2.0. [35]. The training loss is minimized via stochastic gradient descent for the first 5,000 steps, then 10\(^{-4}\) for the next 5,000 steps, then 10\(^{-4}\) for the next 20k, followed by 0.02. We always trained for 100k iterations, unless noted. When training up to 600k iterations, we changed to 0.002 after 430k iterations (as it is default for DeepLabCut).

Speed Benchmarking

We evaluated the inference speed for one video with 11,178 frames at resolutions 512 × 512, 256 × 256 and 128 × 128. We used batch sizes: [1, 2, 4, 16, 32, 128, 256, 512], and ran all models for all 3 (training set shuffles) trained with 50% of the data in a pseudo random order on an NVIDIA Titan RTX. For the benchmarking on a CPU we used shortened the videos to merely 728 frames; the CPU was an Intel Xeon CPU E5-2603 v4 @ 1.70GHz with 6 cores. We also updated the inference code from its numpy implementation [34] to TensorFlow, which brings a 2 – 10% gain in speed.

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FIG. S1. Example frames with human and pretrained network annotations. Here we show the smallest networks, namely ResNet-50 and the ultra-lightweight MobileNetV2-0.35, trained for 100,000 iterations. Top Left set: example training images. Top Right: within domain test image results. Bottom: out-of-domain horses. Examples illustrate the challenges: varying coat colors, size changes, background, human legs, various postures, background horses, and partially occluded horses while they walk in and out of the video frames.
FIG. S2. **Transfer Learning boosts accuracy (PCK).** A: Percent Correct Keypoint (PCK) vs. Training Set Fraction shows high performance for all networks on Horse-10. Darker to light red shades are test results for pretrained networks: ResNet-101, ResNet-50, MobileNetV2-1, MobileNetV2-0.75, MobileNetV2-0.5, MobileNetV2-0.35. Darker to lighter blue is for training, the same ordering as in test. All lines are averages of 3 splits (see Methods). B: Same as in A, plus the out-of-domain data (pink is for out-of-domain data on 20 unseen horses). C: Same as in B, but without pretraining on ImageNet.

FIG. S3. **Test and training performance when training from scratch.** A: Normalized Error vs. Training Set Fraction of Horse-10. 5% is ≈ 160 frames. Darker to light red shades are test results for ResNet-101, ResNet-50, MobileNetV2-1, MobileNetV2-0.75, MobileNetV2-0.5, MobileNetV2-0.35. Darker to lighter blue is for training, same ordering as in test. B: Normalized Error vs. Network performance as ranked by the Top 1% accuracy on ImageNet, but here on Horse-10; namely, MobileNetV2-0.35, MobileNetV2-0.5, MobileNetV2-0.75, MobileNetV2-1, ResNet-50, ResNet-101. Test data is in red, train is blue. This data is for 50% training set fraction.
FIG. S4. Speed Benchmarking for ResNets and MobileNetV2s: Inference speed for videos of different dimensions for all the architectures. A–C: FPS vs. batchsize, with video frame sizes as stated in the title. Three splits are shown for each network. MobileNetV2 gives a more than 2X speed improvement (over ResNet-50) for offline processing and about 40% for batchsize=1 on a Titan RTX GPU. On CPU we found even larger gains.

TABLE S1. Batch size 1 (FPS): Mean inference speed for batchsize=1 and batchsize=256 (Table 2) for there different video frame sizes on a Titan RTX GPU. Video was ≈ 11,000 frames long of a horse, with 22 bodyparts to be identified. See Methods for further details.

| Video Frame Size | MobileNetV2-0.35 | MobileNetV2-0.50 | MobileNetV2-0.75 | MobileNetV2-1 | ResNet-50 | ResNet-101 |
|------------------|------------------|------------------|------------------|--------------|-----------|-----------|
| 128x128          | 195              | 185              | 185              | 190          | 146       | 93        |
| 256x256          | 132              | 131              | 129              | 132          | 99        | 69        |
| 512x512          | 65               | 61               | 55               | 53           | 45        | 34        |

TABLE S2. Batch size 256 (FPS): Mean inference speed; same videos as in Table 1.

| Video Frame Size | MobileNetV2-0.35 | MobileNetV2-0.50 | MobileNetV2-0.75 | MobileNetV2-1 | ResNet-50 | ResNet-101 |
|------------------|------------------|------------------|------------------|--------------|-----------|-----------|
| 128x128          | 2557             | 2338             | 2008             | 1834         | 1208      | 902       |
| 256x256          | 784              | 711              | 568              | 523          | 339       | 249       |
| 512x512          | 176              | 161              | 128              | 118          | 84        | 62        |