Chair Segments: A Compact Benchmark for the Study of Object Segmentation

Leticia Pinto-Alva‡†, Ian K. Torres,*†, Rosangel Garcia§*, Ziyan Yang†, Vicente Ordonez†
‡Universidad Católica San Pablo, †University of Massachusetts, Amherst, §Le Moyne College,
†University of Virginia
lp2rv@virginia.edu, zy3cx@virginia.edu, vicente@virginia.edu

Abstract

Over the years, datasets and benchmarks have had an outsized influence on the design of novel algorithms. In this paper, we introduce Chair Segments, a novel and compact semi-synthetic dataset for object segmentation. We also show empirical findings in transfer learning that mirror recent findings for image classification. We particularly show that models that are fine-tuned from a pretrained set of weights lie in the same basin of the optimization landscape. Chair Segments consists of a diverse set of prototypical images of chairs with transparent backgrounds composited into a diverse array of backgrounds. We aim for Chair Segments to be the equivalent of the CIFAR-10 dataset but for quickly designing and iterating over novel model architectures for segmentation. On Chair Segments, a U-Net model can be trained to full convergence in only thirty minutes using a single GPU. Finally, while this dataset is semi-synthetic, it can be a useful proxy for real data, leading to state-of-the-art accuracy on the Object Discovery dataset when used as a source of pretraining. Baselines and data can be found here: https://github.com/uvavision/chair-segments

1. Introduction

Many model architectures have been proposed for image classification with increasing levels of performance [18, 34, 11, 35, 13]. These advances have been fueled partially by the availability of common benchmarks that have allowed researchers to quickly iterate over model designs [19, 17, 3]. While the ImageNet dataset has brought significant advances, more compact datasets such as CIFAR-10 have allowed the quick exploration of novel ideas that are later validated in larger scale datasets. We aim to capture the simplicity of CIFAR-10 but for object segmentation. Current datasets for segmentation often require models that solve simultaneously object localization and object recognition on top of predicting segmentation masks (e.g. Mask-RCNN [10]). We posit that as a result there is considerably less work in creating specialized segmentation networks that are solely designed to produce high quality segmentation masks (e.g. U-Net [31]).

In this work, we introduce Chair Segments, a semi-synthetic dataset that is compact, reasonably challenging, and has pixel-accurate ground truth segmentations (Figure 1). We focus on chairs, because this object is challenging both structurally and semantically. Chairs have also long interested perceptual psychologists and computer vision scientists because recognizing them requires cues that go beyond shapes and colors but also need to account for affordances [21, 23, 8, 27, 28], i.e. chairs are defined by their functionality. In terms of structure chairs have elongated and complex shapes that could be hard to group. Moreover, we show that complex models such as U-Net can be reliably trained to full convergence in under an hour using a single GPU. We also demonstrate that these models are reliably modeling real-world data by showing state-of-the-art accuracy using transfer learning on the Object Discovery dataset.

Figure 1. Images in the Chair Segments dataset are created semi-synthetically by relying on images of chairs with transparent backgrounds and compositing them on background images to encourage diversity, and reasonably challenging testing conditions. Unlike other datasets, ground truth segmentation masks are pixel-level accurate as they are not hand annotated.

*Work conducted as visiting students at the University of Virginia
dataset (airplanes, horses, and cars) [32]. Finally, we use Chair Segments to replicate findings in the image classification domain where it was shown that models fine-tuned from a set of pretrained weights lie in the same basin of the optimization landscape [25].

Collecting data for image segmentation is considerably costlier than for image classification. Accurate segmentation masks are laborious to annotate even for a single image. Many prior works rely on clicking to obtain object segmentations, where annotators approximate segment masks with a polygon. In our work, we rely on images with transparent backgrounds which are commonly used for e-commerce websites to display shopping items. These images are often captured using a chroma-key backdrop in order to easily and accurately separate the object from its background. By using these type of images we are able to collect thousands of object foregrounds with pixel accurate masks. We generate a dataset with these chair segments by compositing them on a diverse array of background images of scenes, making sure that neither segments nor backgrounds have any overlap between training, validation and testing. A sample of images in this benchmark are shown in Figure 2.

Our paper also serves to validate some of the findings of Neyshabur et al [25] in transfer learning but for image segmentation. Including that models fine-tuned under the same initial pretrained model lie closer in parameter space than models trained from a random set of parameters, and that those fine-tuned models also fall within the same optimization basin compared to models trained from random initialization. As in image classification, fine-tuning also seems to bring benefits both in accuracy through feature reuse and convergence rates due to good initialization.

Our contributions can be summarized as follows:

- We introduce Chair Segments, a semi-synthetic dataset that can be used to benchmark and quickly develop neural network architectures for object segmentation.
- Results showing that Chair Segments is a good source of pretraining for real images by showing state-of-the-art results on the Object Discovery dataset [32].
- Analysis of transfer learning confirming previous empirical results on transfer learning for image classification, signaling that gains in transfer learning for classification area are likely to be beneficial for image segmentation as well.

Our paper is organized as follows: Section 2 discusses related segmentation datasets and use of synthetic datasets in various applications, Section 3 discusses the construction of Chair Segments, Section 4 states the main claims of our work with respect to our provided resource and our findings on transfer learning for segmentation, Section 5 presents our experiments on using Chair Segments and initial benchmarks, Section 6 discusses our findings in transfer learning analysis, and finally Section 7 concludes our paper.

2. Related Work

Our work is related to many previous efforts in collecting datasets for segmentation, and the use of semi-synthetic data for the development of image segmentation models.

Compact Datasets Compact datasets such as CIFAR-10 and CIFAR-100 [17] have been heavily used to develop novel architectures for image classification. We argue that such equivalent dataset is missing for the task of image segmentation. As a result, many developments in models for segmentation have happened as separate efforts e.g. U-Net [31] in the medical image domain, and fully convolutional networks (FCNs) [22] in semantic segmentation. We extensively test FCNs and U-Net models in our proposed Chair Segments benchmark and confirm their relative strength as evidenced in larger scale benchmarks.

Semantic Segmentation Datasets There have been many datasets proposed in the past for semantic segmentation. These datasets usually extend the task of object detection to also include masks, such as the PASCAL VOC Dataset [6], the LabelMe Dataset [33], and more recently the COCO Dataset [20], the KITTI dataset[7], and the ADE20K Dataset [37], among others. Unlike these datasets Chair Segments is built to be compact and pixel-accurate, and does not require to solve the semantic labeling task together with the pixel grouping task. This will allow researchers to concentrate in obtaining good grouping for a specific category while bypassing the need to solve together other problems such as the long-tail problem in segmentation datasets. Moreover, while Chair Segments is smaller in scale, due to its conception, it contains ground truth masks that are of considerably higher quality than existing datasets (see Figure 3). Other compact datasets such as Object-Discovery [32] with excellent pixel accuracy are not large enough to allow for pretraining and explore deeply feature
representation learning for segmentation. There are other datasets in specialized domains such as the INRIA Aerial Image Labeling dataset [24] in remote sensing, and the EM segmentation challenge in medical imaging [2].

**Synthetic Datasets** There have been several previous efforts to use synthetic data to bypass the need to manually annotate images. For instance, dense vector field annotations for benchmarking optical flow algorithms are almost infeasible to be annotated by hand. Datasets such as the Flying Chairs dataset [5] consisting of synthetic scenes, have enabled great progress in this area. For image segmentation, the SAIL-VOS Dataset used a graphics engine from a videogame to render scenes with segmentations [12]. Unlike these datasets based on computer generated imagery, we propose composites of images with transparent backgrounds as supported by the portable network graphics format (PNG) which is widely used on the web to advertise products in image catalogs. Closest to our approach is the previous work of Jin et al [15] that queried images on a search engine for various objects with white backgrounds.

### 3. Data Collection: Chair Segments

Our objective was to collect a compact dataset where model architectures can be tested in a short amount of time, while maintaining a reasonable level of difficulty. We also wanted to isolate the task of segmentation and grouping from issues of categorization. However, we do acknowledge that pixel grouping is a holistic process that requires both low-level features and top-down reasoning [1]. As a result, a generic segmentation model that is category independent is unlikely to be realized, therefore we aimed to collect a category specific segmentation resource that is instead diverse in terms of shapes and challenging in terms of visual complexity. Chairs have challenging and highly intricate shapes for image segmentation, as they often contain thin and elongated parts, hollow segments, and self-occluding parts. Moreover chairs are the hardest categories in current benchmarks such as the Pascal VOC segmentation task\(^1\) where the top performer achieves an average overall precision of 90.5 but only 57.5 precision for the chair category.

We queried images using the Google search engine and restrict the search results to only images with transparent backgrounds. In order to ensure diversity we issue queries for chairs by relying on pairs of words from the LEVAN ontology [4] which was compiled in a data driven fashion. Queries included things such as “arm chair”, “accent chair”, “swivel chair”, “office chair”, “dining chair”, etc. Then we manually filtered out images that did not contain transparent backgrounds, did not contain relevant images, or contained more than one chair in the same image. Most of the remaining chairs have masks that are of the highest accuracy as these are often used in e-commerce and are captured in controlled conditions with chroma-key backdrops and/or multiple camera settings for clean and effective background removal. Using this process we ended up with 900 chair segments by dropping the pixels indicated by the transparent background. Similarly, we selected a random subset of 10,000 background scene images following a similar protocol as in the Houzz Dataset [29] but also ensuring diversity across different types of indoor and outdoor scenes in a house environment. In this way, we encourage our foregrounds and backgrounds to be somewhat semantically consistent. Our final dataset will be released publicly along with code to replicate our current benchmarks.

We split the chair segments into 500 for the training split, 200 for the validation split, and 200 for the testing split. Similarly, we split the background images into three groups containing 60% for the training split, 20% for the validation split and 20% for the testing split. Then we create composites for the training set, by pairing each of the 500 chair segments in this split with 100 randomly selected backgrounds in the training split for every chair, resulting in a total of 50,000 image composites for the training set. We follow a similar process to generate composite images for the validation and testing set, to obtain 20,000 for each of them.

We generate composites at several resolutions by first resizing the background image into a target \(d \times d\) resolution, and then alpha blending (with the transparent background mask) with a given chair segment that is first resized to a \((d - k) \times (d - k)\) resolution where \(k\) is a padding size that is left around the chair segment. We create several versions of our dataset at various resolutions: \(32 \times 32, 64 \times 64, 128 \times 128,\) and \(256 \times 256,\) using padding sizes of 3, 6, 13, and 26 pixels respectively for each resolution.

---

\(^1\)Pascal VOC Segmentation task. Retrieved on November 2020. 
[http://host.robots.ox.ac.uk:8080/leaderboard/displaylb_main.php?challengeid=11&compid=6.](http://host.robots.ox.ac.uk:8080/leaderboard/displaylb_main.php?challengeid=11&compid=6)
4. Main Claims

In the rest of the paper we aim to demonstrate three main claims related to the proposed resource and transfer learning in image segmentation more broadly:

- Chair Segments is challenging while allowing fast benchmarking (in a few hours) for modern neural network architectures designed for image segmentation such as U-Net [31] and FCNs [22].
- Chair Segments despite being semi-synthetic, represents well the type of learning required for real datasets as evidence by state-of-the-art results on the Object Discovery Dataset [32] through transfer learning. We also compare pretraining on chair images from the existing COCO dataset vs pretraining on our proposed Chair Segments dataset with favorable results.
- Transfer learning in image segmentation exhibits similar properties to those recently found in the transfer learning process for image classification [25].

The first claim is important as a trivial dataset could be potentially limited in its lifetime. However at this point it is worth noting that even datasets such as MNIST [19] have withstood the test of time despite being considered largely “solved” – where many modern approaches can reach accuracies close to the maximum possible. That said, we do show that Chair Segments is reasonably challenging with the top performing model obtaining an IoU of 85.08 at our target standard resolution of 64 × 64 pixels. We further demonstrate the validity and usefulness of Chair Segments by showing that models that are more performant on large scale benchmarks are also more performant on Chair Segments (e.g. U-Net outperforms vanilla FCNs).

The second claim is demonstrated by showing that by simply fine-tuning models pretrained on Chair Segments for a smaller dataset of real images. We demonstrate this by fine-tuning models on the Object Discovery Dataset [32] which contains three categories unrelated to chairs: horses, cars, and airplanes. A fine-tuned U-Net model yields state-of-the-art results on all metrics.

The third claim is demonstrated by replicating the experiments from Neyshabur et al [25] that demonstrate that under transfer learning, models tuned on a smaller dataset share certain properties such as fine-tuned models lying in the same optimization basin despite being trained under stochastic gradient descent (SGD). Our work is the first to empirically demonstrate these properties for transfer learning in image segmentation.

5. Experiments

We consider two approaches for image segmentation resulting in four different models. The first is the fully-convolutional network (FCN) approach [22] consisting of standard neural network architectures for classification where the last layers are replaced with an upsampling layer that produces a 2D output instead of classification scores. The second approach we consider is U-Net [31], consisting of encoder-decoder modules containing multiple downsampling and upsampling operators respectively with skip-connections to preserve high-resolution information across the network which has proved essential for segmentation. Our implementation of U-Net also relies on zero padding in order to be used with low resolution inputs. For the FCN approach we consider three variants leveraging various neural network architecture backbones, VGG-16 [34], ResNet-50, and ResNet-101 [11]. We denote the resulting four models in our experiments as: FCN-VGG-16, FCN-ResNet-50, FCN-ResNet-101, and U-Net.

We use three standard metrics for image segmentation in our experiments: Precision also known as per-pixel accuracy, which simply consists in the percentage of pixels in the image that were classified correctly; Jaccard Index also known as Intersection-Over-Union (IoU), which is the area of overlap between the predicted segmentation and the ground truth divided by the area of their union; and Dice Coefficient, also known as F1 score, which can be computed as $2 \times$ the area of overlap divided by the total number of pixels between the ground truth segmentation and the segmentation predicted by the model. These are all three widely used metrics in this area.

5.1. Training Time Trade-Offs

First, we measure how quickly we can train to full convergence some of our models in the Chair Segments dataset and whether they are able to achieve a reasonable accuracy. We train U-Net, FCN-VGG-16 and FCN-ResNet-50 models on the Chair Segments dataset for all resolutions and train until convergence by early stopping if the IoU metric has not changed in the past few training steps. We show results on Table 1 including time to convergence and the maximum IoU score achieved.

We particularly found that U-Net can reach full convergence in four epochs in about 30 minutes for the $64 \times 64$ resolution, and in four epochs in about 1 hour for the $128 \times 128$ resolution. Based on these results, we decided to use the $64 \times 64$ resolution for the remaining experiments on the paper and this will be the recommended resolution to be used for future benchmarking. Note that this is only four times the resolution of images in the CIFAR-10 dataset that are scaled at a resolution of $32 \times 32$.

5.2. Benchmarking on Chair Segments

We benchmark all four models on Chair Segments at the fixed resolution of $64 \times 64$. For FCN-VGG-16 we train with a learning rate of 1e-4, using standard stochastic gradient descent and a per pixel binary cross entropy loss. For
the FCN-ResNet-50 and FCN-ResNet-101 models, we use a learning rate of 1e-5, with an RMSprop optimizer, momentum of 0.9, weight decay of 1e-6, and a per pixel binary cross entropy loss. For the U-Net model, we use a learning rate of 1e-3 with an Adam optimizer, and a per pixel binary cross entropy loss.

Results. Table 2 shows the results for all these models across all metrics. We observe that U-Net is the top performing model by a considerable margin, followed by FCN-ResNet-101, FCN-ResNet-50 and FCN-VGG-16. Thus, demonstrating that our benchmark represents well the difficulties of larger benchmarks with respect to top performing models for image segmentation. Figure 4 shows example results for these models along with the input images and ground truth segmentation masks. We observe that FCNs coupled with classification networks seem to be learning the right masks but they fail to capture finer level details as these networks were mostly designed for image classification. This is especially clear for the ResNet networks which due to their depth they inherently tend to lose high-resolution information along their computation path and multiple steps of downsampling. On the other hand, U-Net having multiple downsample and upsample steps coupled with skip connections manages to retain high-resolution information much better than the other models. This implementation of U-Net also avoids boundary issues through zero padding.

Is Chair Segments solved? The top performing U-Net model achieves a precision of 97.18, however a zero-knowledge baseline that blindly assigns every pixel as background would achieve a precision of 78.01 on this dataset. The IoU metric (intersection over union) is therefore much more informative and even the best model achieves 85.08 in this score. Models that are not able to generate precise high resolution masks lag considerably behind on this metric. We consider that models achieving IoUs squarely above 90 will be an open area of investigation and this benchmark is unlikely to saturate soon. We expect that this leaves room for future improvements both in terms of stronger model architectures for segmentation and faster models for real time deployment.

5.3. Fine-tuning on the Object Discovery Dataset

The Object Discovery dataset introduced by Rubinstein et al [32] for object segmentation contains images with ground truth masks for three types of objects: cars, horses and airplanes. This dataset although small, has been used over the years to test from handcrafted methods based on energy-based minimization and graphical models, to more recent neural network architectures for segmentation. We train our four considered models on this dataset in two conditions: from randomly initialized weights, and from weights pretrained on Chair Segments. Additionally, we train the best model (U-Net) with chair segments obtained from the COCO Segments dataset (COCO Chairs) instead of our dataset. Our goal is to measure whether Chair Segments provides useful transfer learning information for this task.

For FCN-VGG-16 we train with a learning rate of 1e-4, an SGD optimizer with per pixel binary cross entropy loss. For the FCN-ResNet-50 model we use a learning rate of 1e-4, an SGD optimizer with momentum of 0.9, weight decay of 1e-5, and a per pixel binary cross entropy loss. For the FCN-ResNet-101 model we use a learning rate of 1e-5, an RMSprop optimizer with a momentum of 0.9, weight decay of 1e-6, and a per pixel binary cross entropy loss. Finally, for U-Net we use a learning rate of 1e-3, and an Adam optimizer with a per pixel binary cross entropy loss. These hyperparameters were determined using the validation split through standard hyperparameter tuning.

Results and Discussion. Table 3 shows results for all the models both when training from scratch (from randomly initialized weights), and when fine-tuning from a model pretrained on the Chair Segments dataset. We additionally show results for U-Net when pretrained on COCO Chairs.

### Table 1

| Model       | Resolution | 32×32 | 64×64 | 128×128 | 256×256 |
|-------------|------------|-------|-------|---------|---------|
|             | time       | IoU   | time  | IoU     | time    | IoU     |
| U-Net       | 6.4        | 91.68 | 9.1   | 68.38   | 0.5     | 85.08   |
| FCN-VGG-16  | 2.1        | 60.75 | 2.7   | 61.09   | 3.6     | 74.55   |
| FCN-ResNet-50 | 5.5      | 53.59 | 19.3  | 60.19   | 10.1    | 70.94   |
| FCN-ResNet-101 | 92.19   | 61.62 | 74.09 | 10.1    | 70.94   |

Table 1. This table shows the time in hours and the number of epochs that each model required to converge on Chair Segments under various resolutions. For instance, a model such as U-Net can be trained to convergence in about 30 minutes on images at a 64×64 resolution.

### Table 2

| Model       | Prec.  | IoU   | Dice  |
|-------------|--------|-------|-------|
| U-Net       | 97.18  | 85.08 | 91.25 |
| FCN-VGG-16  | 91.73  | 61.09 | 74.09 |
| FCN-ResNet-50 | 92.04  | 60.19 | 72.58 |
| FCN-ResNet-101 | 92.19  | 61.62 | 73.96 |

Table 2. Benchmarking results of different models on the Chair Segments dataset. U-Net is the top performing method while fully convolutional networks (FCNs) trail in all metrics depending on the feature backbone used.
We observe as in the Chair Segments dataset, that U-Net is the superior model across all experiments, and fine-tuning helps in almost all subsets of this dataset under all metrics, and often by a considerable margin especially on the IoU metric which is the most important for segmentation quality. Moreover, U-Net pretrained on the Chair Segments dataset outperforms U-Net pretrained on COCO Chairs, further demonstrating that Chair Segments is a valuable resource and is able to represent well a segmentation task with real-world images despite being semi-synthetic.

Table 4 shows our top performing models U-Net and U-Net pretrained on Chair Segments when compared against all previous methods in the research literature, establishing these two models as the state-of-the-art under this benchmark. Figure 5 shows qualitative results on this benchmark for a few examples along with results released with this dataset [32] using a hand-crafted approach. We can see that FCN-ResNet-101 still struggles with finer-level details while U-Net is able to produce masks at a much higher resolution. However, even U-Net seems to be assigning some pixels as foreground when they are clearly disconnected or dissimilar from the object, which leaves room for future improvement in model designs that can better preserve finer-level structures.

6. Transfer Learning Analysis

There has been recent work in image classification to analyze the extent to which transfer learning helps in tasks that have access to less amounts of training data [26, 9, 16, 25]. More specifically, there is a growing interest to analyze to what extent does transfer learning help with providing a better starting point for optimization and to what extent feature reuse is the driving factor. We adopt the recently proposed framework of Neyshabur et al [25] which allows us to directly draw analogies between transfer learning in image classification and transfer learning in segmentation.
| Model                  | Car Prec. | Car IoU | Horse Prec. | Horse IoU | Airplane Prec. | Airplane IoU |
|------------------------|-----------|---------|-------------|-----------|----------------|--------------|
| Rubinstein et al.[32]  | 85.4      | 0.64    | 82.8        | 0.52      | 88.0           | 0.56         |
| Quan et al.[30]        | 88.5      | 0.67    | 89.3        | 0.58      | 91.0           | 0.56         |
| Jerripothula et al.[14]| 88.0      | 0.71    | 88.3        | 0.61      | 90.5           | 0.61         |
| Yuan et al.[36]        | 90.4      | 0.72    | 90.2        | 0.65      | 92.6           | 0.66         |
| U-Net                  | 95.7      | 0.86    | 93.5        | 0.66      | 94.6           | 0.65         |
| U-Net (w/ pretraining) | 96.4      | 0.88    | 94.5        | 0.71      | 94.5           | 0.72         |

Table 4. U-Net pretrained on Chair Segments obtains the state-of-the-art in the Object Discovery dataset.

We show in Figure 6 a plot averaging two runs of our U-Net model training from scratch, and fine-tuned from pretrained weights across training steps until convergence. We can observe that not only the pretrained model is reaching a higher IoU score but it also reaches a value close to convergence much faster than the same network trained from random parameters. Hence we can see that both feature reuse and good initialization are driving factors – confirming results obtained for image classification. This result might seem trivial but we would like to emphasize the discrepancy in the source and target domains, where the source domain only contains chair images and chair segments, while the target domain only contains, horses, cars and airplanes.

There are two additional findings that we present in this section: (1) Analyzing how far apart are comparable pretrained models and models trained from scratch in terms of $\ell_2$ distances, and (2) Exploring the linear interpolation space between models trained from pretrained weights, and models trained from random initialization. In both cases, we found that the results we obtain confirm those obtained for image classification in Neyshabur et al.[25]. These results could lead to better algorithms for initializing neural networks for segmentation and for optimizing ensembles of models that lie within close areas in the optimization landscape.

6.1. Analyzing Model Distances in Parameter Space

Table 5 shows $\ell_2$ distances in parameter space between two models fine-tuned from the same set of pretrained weights (Ft & Ft) for both image classification and image segmentation (first column), similarly we compute $\ell_2$ distances between two models trained from randomly initialized weights (Ri & Ri) for both tasks (second column), and between a model fine-tuned from pretrained weights and the
pretrained network itself (Ft & P) for both tasks (column 3), and between a network trained from randomly initialized weights and a pretrained network (Ri & P) (last column). For all segmentation models we used the U-Net neural network architecture.

The results are strikingly similar as those obtained for image classification by [25], suggesting that improved methods for transfer learning in image classification are likely to lead to gains in image segmentation as well. And more importantly for us, that our fine-tuned models behave similarly as models fine-tuned from Imagenet pretrained models for image classification on a smaller dataset – which suggests that Chair Segments is useful as a proxy for real world data. To summarize these results, it seems models that are trained from the same initialization from pretrained weights end up lying closer in parameters space, than models that started from random weights instead. As a sanity check, unsurprisingly, models that are fintuned, are closer in parameter space from their starting point pretrained network (Ft & P) compared to models trained from scratch (Ri & P).

### 6.2. Analyzing the Loss Landscape of Models

Finally, we analyze the behavior of our pair of models (Ft & Ft), both trained from the same checkpoint P, we shall denote them more formally here $F_1$ and $F_2$, and the two models trained from randomly initialized weights (Ri & Ri), we shall denote them more formally here as $S_1$ and $S_2$. As in the previous section, for all models we used the U-Net neural network architecture.

Let $W_1$ and $W_2$ be two different set of weights for models $F_1$ and $F_2$, then we can define a new model $F_\alpha$ that is a model with a set of parameters $W_\alpha = \alpha W_1 + (1 - \alpha)W_2$, where $\alpha$ is an interpolation scalar parameter between 0 and 1. Therefore $F_\alpha$ is a model that lies in the linear interpolation space between $F_1$ and $F_2$. We define in the same way a model $S_\alpha$ with respect to $S_1$ and $S_2$. The question we are trying to assess is: Are models that lie in between these two models found through stochastic gradient descent any good? If the loss landscape where the two models ($S_1$, $S_2$) or ($F_1$, $F_2$) lie within a flat landscape, then the transition must be smooth and intermediate models should be performant. We found this to be the case only for the pair of models ($F_1$, $F_2$) as evidence in our Figure 7 where we can clearly observe that randomly initialized models quickly degrade when moving away from the starting points, while fine-tuned models transition smoothly without loss in IoU scores. These results confirm the results in transfer learning obtained for Imagenet pretrained networks on transfer learning as evidenced in [25].

![Figure 7. We show that two models that are fine-tuned from the same pretrained model lie within the same optimization basin with respect to a linear interpolation, while the same is not true for two models trained from scratch.](image)

### 7. Conclusions

We can conclude that our Chair Segments benchmark is a useful dataset that presents consistent results over different image segmentation methods and can be a useful resource to develop new models and algorithms for image segmentation that can later be applied to semantic image segmentation or semantic instance segmentation. Also, our study of transfer learning over image segmentation give us the opportunity for a better understanding of how deep neural networks behave when fine-tuned for a target task with more constrained numbers of training samples – mirroring results observed in the more well studied problem of image classification. As a result of our experiments we are planning to apply variations of our current U-Net model to either obtain more performant models or devising new methods for optimizing models that take better advantage of the properties of transfer learning.

**Acknowledgments** We thank the UVA Department of Computer Science in Partnership with DREU CRA-W, for hosting and funding I.K.T and R.G. through NSF #CNS-1246649, IAAMCS. This work was also partially funded with generous gifts from Leidos and Adobe.
References

[1] Pablo Arbelaez, Michael Maire, Charless Fowlkes, and Jitendra Malik. From contours to regions: An empirical evaluation. In 2009 IEEE Conference on Computer Vision and Pattern Recognition, pages 2294–2301. IEEE, 2009. 3

[2] Ignacio Arganda-Carreras, Srinivas C Turaga, Daniel R Berger, Dan Cireșan, Alessandro Giusti, Luca M Gambardella, Jürgen Schmidhuber, Dmitry Laptev, Sarvesh Dwivedi, Joachim M Buhmann, et al. Crowdsourcing the creation of image segmentation algorithms for connectomics. Frontiers in neuroanatomy, 9:142, 2015. 3

[3] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition, pages 248–255. Ieee, 2009. 1

[4] Santosh K Divvala, Ali Farhadi, and Carlos Guestrin. Learning everything about anything: Weby-supervised visual concept learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3270–3277, 2014. 3

[5] Alexey Dosovitskiy, Philipp Fischer, Eddy Ilg, Philip Hausser, Caner Hazirbas, Vladimir Golkov, Patrick Van Der Smagt, Daniel Cremers, and Thomas Brox. Flownet: Learning optical flow with convolutional networks. In Proceedings of the IEEE international conference on computer vision, pages 2758–2766, 2015. 3

[6] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. International journal of computer vision, 88(2):303–338, 2010. 2

[7] Andreas Geiger, Philip Lenz, Christoph Stiller, and Raquel Urtasun. Vision meets robotics: The kitti dataset. The International Journal of Robotics Research, 32(11):1231–1237, 2013. 2

[8] Helmut Grabner, Juergen Gall, and Luc Van Gool. What makes a chair a chair? In CVPR 2011, pages 1529–1536. IEEE, 2011. 1

[9] Kaiming He, Ross Girshick, and Piotr Dollár. Rethinking imagenet pre-training. In Proceedings of the IEEE international conference on computer vision, pages 4918–4927, 2019. 6

[10] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In Proceedings of the IEEE international conference on computer vision, pages 2961–2969, 2017. 1

[11] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016. 1, 4

[12] Yuan-Ting Hu, Hong-Shuo Chen, Kexin Hui, Jia-Bin Huang, and Alexander G Schwing. Sail-vos: Semantic amodal instance level video object segmentation-a synthetic dataset and baselines. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3105–3115, 2019. 3

[13] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4700–4708, 2017. 1

[14] Koteswar Rao Jerrapothula, Jianfei Cai, and Junsong Yuan. Image co-segmentation via saliency co-fusion. IEEE Transactions on Multimedia, 18(9):1896–1909, 2016. 7

[15] Bin Jin, Maria V Ortiz Segovia, and Sabine Susstrunk. Weby supervised semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3626–3635, 2017. 3

[16] Simon Kornblith, Jonathon Shlens, and Quoc V Le. Do better imagenet models transfer better? In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2661–2671, 2019. 6

[17] Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton. Cifar-10 and cifar-100 datasets. URL: https://www.cs.toronto.edu/kriz/cifar.html, 6:1, 2009. 1, 2

[18] Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, pages 1097–1105, 2012. 1

[19] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11):2278–2324, 1998. 1, 4

[20] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer, 2014. 2

[21] Toby J Lloyd-Jones and Glyn W Humphreys. Categorizing chairs and naming pears: Category differences in object processing as a function of task and priming. Memory & Cognition, 25(5):606–624, 1997. 1

[22] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3431–3440, 2015. 2, 4

[23] Gary Lupyan. From chair to “chair”: A representative shift account of object labeling effects on memory. Journal of Experimental Psychology: General, 137(2):348, 2008. 1

[24] Emmanuel Maggiori, Yuliya Tarabalka, Guillaume Charpiat, and Pierre Alliez. Can semantic labeling methods generalize to any city? the inria aerial image labeling benchmark. In IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE, 2017. 3

[25] Behnam Neyshabur, Hanie Sedghi, and Chiyuan Zhang. What is being transferred in transfer learning? arXiv preprint arXiv:2008.11687, 2020. 2, 4, 6, 7, 8

[26] Jiquan Ngiam, Daiyi Peng, Vijay Vasudevan, Simon Kornblith, Quoc V Le, and Ruoming Pang. Domain adaptive transfer learning with specialist models. arXiv preprint arXiv:1811.07056, 2018. 6

[27] Vicente Ordonez, Vignesh Jagadeesh, Wei Di, Anurag Bhardwaj, and Robinson Piramuthu. Furniture-geek: Unsupervised semantic transfer learning with specialist models. arXiv preprint arXiv:1811.07056, 2018. 6
[28] Luisa F. Polania, Mauricio Flores, Matthew Nokleby, and Yiran Li. Learning furniture compatibility with graph neural networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, June 2020.

[29] Omid Poursaeed, Tomáš Matera, and Serge Belongie. Vision-based real estate price estimation. Machine Vision and Applications, 29(4):667–676, 2018.

[30] Rong Quan, Junwei Han, Dingwen Zhang, and Feiping Nie. Object co-segmentation via graph optimized-flexible manifold ranking. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016.

[31] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention, pages 234–241. Springer, 2015.

[32] Michael Rubinstein, Armand Joulin, Johannes Kopf, and Ce Liu. Unsupervised joint object discovery and segmentation in internet images. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), June 2013.

[33] Bryan C Russell, Antonio Torralba, Kevin P Murphy, and William T Freeman. Labelme: a database and web-based tool for image annotation. International journal of computer vision, 77(1-3):157–173, 2008.

[34] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

[35] C Szegedy, W Liu, Y Jia, P Sermanet, SE Reed, D Anguelov, D Erhan, V Vanhoucke, and A Rabinovich. Going deeper with convolutions, corr, vol. abs/1409.4842, 2014.

[36] Ze-Huan Yuan, Tong Lu, and Yirui Wu. Deep-dense conditional random fields for object co-segmentation. In IJCAI, pages 3371–3377, 2017.

[37] Bolei Zhou, Hang Zhao, Xavier Puig, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Scene parsing through ade20k dataset. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 633–641, 2017.