Learning Densities in Feature Space for Reliable Segmentation of Indoor Scenes

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Abstract: Deep learning has enabled remarkable advances in semantic segmentation and scene understanding. Yet, introducing novel elements, called out-of-distribution (OoD) data, decreases the performance of existing methods, which are usually limited to a fixed set of classes. This is a problem as autonomous agents will inevitably come across a wide range of objects, all of which cannot be included during training. We propose a novel method to distinguish any object (foreground) from empty building structure (background) in indoor environments. We use normalizing flow to estimate the probability distribution of high-dimensional background descriptors. Foreground objects are therefore detected as areas in an image for which the descriptors are unlikely given the background distribution. As our method does not explicitly learn the representation of individual objects, its performance generalizes well outside of the training examples. Our model results in an innovative solution to reliably segment foreground from background in indoor scenes, which opens the way to a safer deployment of robots in human environments.

Keywords: Semantic Segmentation, Deep Learning, Normalizing Flow

1 Introduction

Deep learning methods have allowed significant improvements in computer vision and semantic segmentation tasks in robotic applications [1, 2, 3]. Yet, an important drawback of current Deep Neural Networks trained for classification or segmentation is that they are trained to recognize a fixed set of classes with a limited number of examples. Thus, they behave poorly and unpredictably when they are given out-of-distribution (OoD) examples [4, 5, 6]. Moreover, in such cases, networks often give wrong predictions with high confidence. Although a majority of visual recognition systems are designed for a static closed world, these algorithms aim to be deployed in the dynamic and ever-changing real world [7]. The diversity and variability of our world makes algorithms designed to perform static closed set recognition unsafe and limits the deployment of robotic systems in our everyday tasks [8]. This is particularly important in indoor environments, where diverse objects are often added, moved, or altered. Most autonomous robots designed to operate in the presence of humans will be in such settings. In indoor scenes, background consists of the basic room structure (floor, walls, ceiling, windows), which remains static. Foreground then contains all the dynamic elements (objects, furniture, people etc.), which are prone to much more variability and novelty. For reliable applications of indoor robotics, it is critical to segment such dynamic or novel elements from the background rather than identifying their nature. Classical semantic segmentation is not well suited for this task as it relies on the strong assumption that all objects in the foreground are known a priori [7]. A good way of separating all dynamic objects from the static background would be to use a reliable binary background-foreground segmentation.

We introduce a novel method to segment foreground from background, without having to limit foreground objects to a fixed set. Using images containing only background, we extract feature descriptors, which are simply the output of a deep layer of a convolutional neural network (CNN). These descriptors characterise the background appearance in a high dimensional space and are distributed according to a complex unknown distribution. Leveraging recent advances in flow-based
generative models [9, 10, 11], we use normalizing flow techniques to model this distribution, as done in [12]. Foreground objects are then recognized as having descriptors unlikely to come from the estimated background distribution. We benchmark our results by comparing them with a k-Nearest-Neighbours (kNN) kernel density approach and a classical Fully Connected Network (FCN) segmentation. Results show that our method outperforms both kNN and FCN in average recall and average precision by at least 10% and 17%, respectively, on the validation set.

The novelty of our method is that the training of the segmentation relies solely on background, which has a low variability. Its performance is therefore less affected by the high variability of foreground and it does not assume a limited set. To assess the reliability of our method, we create a validation dataset containing novel objects. The performance drop between test and validation on all evaluated metrics is 1.5 to 10 times larger for a classic FCN segmentation compared to our method.

In summary, our contributions are the following:

- Introduction of a novel method using feature density estimation to perform binary foreground background segmentation in indoor scenes.
- Quantitative and qualitative experiments showing that our method has more reliable performance than a FCN segmentation under the high variability found in indoor scenes.
- Comparison between kNN and normalizing flow showing the superiority of the latter to approximate complex probability distributions.

2 Related Work

2.1 Supervised Semantic Segmentation and Object Detection

Leveraging recent advances in deep learning, state-of-the-art methods in semantic segmentation are comprised of fully-convolutional networks trained with pixelwise supervision [13]. These methods use an encoder-decoder architecture [14, 15], where the role of the decoder network is to map the low resolution encoder features to full input resolution pixelwise classification. In our work, we estimate the probability that the encoder’s features were generated by background to create a background likelihood map, which we can then segment to obtain a binary pixelwise semantic segmentation.

Semantic segmentation techniques are commonly used for object detection. For example, Mask R-CNN [16] uses faster R-CNN [17] to generate Regions of Interest (ROIs) likely to contain objects and then predicts per-pixel semantically annotated masks inside all ROIs. [18] uses depth information to refine the predictions of Mask R-CNN and build 3D maps of indoor environments. Our method does not rely on any object detector like faster R-CNN and does not use depth information. [19] uses RGB-D inputs to perform semantic segmentation of objects on the NYU V2 dataset. They remap the 894 labels of NYU into 14 classes (objects, furniture, wall, ceiling etc.), which illustrates one of the big drawbacks of classical object detectors: they are limited to a fixed set of classes. In contrast, our method is designed to work with an unlimited number of different foreground objects. Another drawback of classical segmentation methods is that they need a large amount of labeled data, which is expensive and difficult to obtain. [20] uses synthetic data to get state-of-the-art performance in segmenting the NYU V2 dataset. Mask R-CNN [21] adopts a transfer method which only requires a subset of the data to be labeled at training time. Large amounts of labeled data are required to perform background foreground segmentation to capture the variability and complexity in foreground objects. However, since our approach relies solely on background, we need fewer data and we can use images of fully empty rooms which do not need to be labeled.

While a lot of research aims to improve the efficiency of object detection [17] and semantic segmentation, few of them focus on their reliability to OoD data. Moreover, despite the amount of work in object detection and scene understanding, the related problem of detecting all foreground objects has not yet been fully addressed. Our results show that our solution provides a way to increase reliability of binary segmentation networks, allowing better generalization on OoD data.

2.2 Novelty and Out-of-Distribution (OoD) detection

Although Bayesian deep learning allows uncertainty representation in settings such as regression or classification [22, 23], non-Bayesian approaches for novelty detection have recently become more popular. [24] for instance combines the k-nearest neighbors algorithm with representations of the
data learned by each layer of the network in order to identify inputs outside the model. Compu-
tationally more efficient alternatives include density estimation and generative probabilistic modelling
methods [25, 6, 10, 11], which allow one to estimate the likelihood of samples with respect to the
ture data distribution and learn meaningful features while requiring little supervision or labeling.
[12] shows great potential in using flow-based approaches [10] to approximate the probability dis-
tribution of deep convolutional features to identify OoD data inside images, generating a binary
segmentation between known and unknown data. Inspired by these works that estimate density
distributions of high dimensional features, we propose a novel application of normalizing flow for
reliable segmentation of foreground and background.

2.3 Normalizing Flow
The data of interest in deep learning frameworks is generally high-dimensional and highly struc-
tured. The challenge in modelling high-dimensional densities for this data is that we need models
powerful enough to capture its complexity but yet still be trainable and efficient. Flow-based mod-
els, first described in [9] (NICE) and later improved in [10] and [11] are known for their generative
properties but can also be used for efficient and exact computation of high dimensional complex
density estimation using the change of variable formula. We use this tool to estimate the probability
distribution of background features.

3 Method
Our work introduces a new way of segmenting background from foreground in indoor scenes. Prior
approaches use labeled datasets to learn pixelwise classifications given foreground objects and back-
ground scenes in a training set. Although these approaches work well when scenes contain the ob-
jects they were trained for, their behavior is unpredictable if we introduce new elements. To tackle
this issue, we suggest a different method that learns only the background appearance of indoor
rooms. This is done in two steps:

• First, we use a convolutional neural network, coined expert network, in order to generate features
from indoor images (section 3.1). Our background descriptors (or features) are simply the output
of a convolution layer in the expert network, and are thus points in a high-dimensional space.

• We then learn what the background in our training set “looks like”. To do so, we use the back-
ground features extracted with the expert network and estimate their probability distribution using
normalizing flow [10] (section 3.2).

When feeding an image of dimension $H \times W \times C$ ($H$ the height, $W$ the width and $C$ the number
of channels) to our network, the expert model transforms it to a feature map of size $h \times w \times f$
(where, for 2x2 pooling filters, $h = H/2^{(# pooling layers)}$, $w = W/2^{(# pooling layers)}$ and $f$ is the feature dimension,
which depends on the architecture of the expert model). Using our approximated background feature
distribution, we can transform the feature map into a likelihood map of dimension $h \times w \times 1$.
We furthermore use bilinear interpolation to upscale the likelihood map back to the original image
dimensions ($H \times W \times 1$). Foreground objects are then simply detected as areas of low probability
in the image and a binary segmentation can be obtained by thresholding the density map.

The strength of our method is that it detects foreground objects in an indoor scene without ever
explicitly learning their appearance, as long as the features associated to them differ from those of
the background. It therefore does not require a training set of foreground elements and does not
limit us to recognizing a fixed set of objects. Our complete pipeline is illustrated in figure 1.

3.1 Feature extraction
Collecting background data:
Ideally, we would train our network on fully empty rooms, but such a dataset does not exist. Instead,
we use a dataset of labeled indoor images (NYU Depth v2 [26]) and generate binary masks to differ-
entiate the background from the foreground. The dataset contains a large number of specific labels,
which we map to background or foreground. We define background to be what an empty room
would contain (ceiling, floor, wall, window). Any other object is then considered as foreground.
With this label mapping, we create a binary mask for each image of the dataset.
Feature extraction: generate background features from indoor images by extracting and thresholding the output of a convolution layer in the expert network. Layer 6 is the concatenation between the output of layer 4 and the (upsampled) output of layer 5.

Density estimation: estimate the probability distribution of the background features using normalizing flow.

**Figure 1:** Illustration of our method.

**Expert Network:**
Our expert network is a fully-convolutional network (FCN) [13], which consists of a VGG-16 encoder [27] followed by a deconvolution. This is a classical architecture for segmentation tasks, which we use in two ways: (i) given the NYU dataset with binary masks as described above, we train this network to perform background-foreground segmentation; (ii) we also show that training of the expert model is not necessary by using weights from a standard VGG-16 trained on ImageNet. In this work, we refer to these two approaches as using (i) NYU segmentation and (ii) ImageNet.

**Feature Mapping:**
We extract features from a chosen layer of the expert network. After convolutions and pooling, features from deep layers will have a large receptive field and are thus likely to have been affected by both background and foreground. To determine which label has most influenced the features, we give them a score between 0 and 1: a high score represents a large proportion of background pixels in the receptive field. We then use a threshold to assign the labels “foreground”, “background” or “mixed” to all features, as shown on figure 1a. Finally, we discard features with foreground and mixed labels to create a dataset of background features, on which we perform density estimation.

3.2 Density Estimation

Given a dataset of background features, our method relies on estimating its probability density distribution. We propose a flow-based approach for this task, which we will compare with kNN.

**kNN Density Estimation:**
Different works [24, 28] use the distance between a test feature and its $k$ nearest training features to estimate uncertainty in neural networks. Similarly, we use kNN to approximate the likelihood of a feature belonging to background. This likelihood is computed using the distances $\text{dist}_k$ to the $k$-th closest background representation: $\text{likelihood} = \frac{1}{k} \sum_{k} \exp(-\text{dist}_k)$. Intuitively, if a feature lies in a part of the space far from any background feature, it is very unlikely to correspond to background. However, this method is computationally inefficient [29].
Flow-Based Density Estimation:
Flow-based approaches like RealNVP [10] have proven to be a good way of estimating complex high dimensional densities. Let \( x \in X \) be one of our high dimensional background descriptors with a complex and unknown distribution \( p_X(x) \). We aim to find a bijective transformation \( f \) that maps \( x \) to a latent space \( z \), where \( p_Z \) is the prior probability distribution of the latent variable, typically chosen to be a simple and tractable density such as a multivariate Gaussian. The transformation \( f \) is constructed by a sequence of simpler bijective transformations: \( f = f_1 \circ f_2 \circ ... \circ f_N \), which is called a (normalizing) flow. In this work, our flow is made of 32 chained transformations. As explained in [10], the scale and translation operations in the bijective transformations \( f_i \) are arbitrarily complex functions, thus modeled as deep neural networks. These networks contain a set of weights \( \theta \), and we call \( p_\theta \) the approximation of \( p_X \). The weights \( \theta \) are learned by minimizing the negative log likelihood (NLL) (under probability \( p_\theta \)) of all background features.

\[
\min_\theta \frac{1}{|X|} \sum_i \log p_\theta(x^{(i)}) \quad \text{where: } \log(p_\theta(x)) = \log(p_z(f(x))) + \log \left( |\frac{\partial f(x)}{\partial x^T}| \right) \tag{1}
\]

The NLL is obtained by using the change of variable formula, and requires efficient computation of the determinant of \( \frac{\partial f(x)}{\partial x^2} \), which is the Jacobian of \( f \) at \( x \). NICE [9] introduces a family of bijective transformations called coupling layers for which the Jacobian is a triangular matrix. As the determinant of a triangular matrix is simply the product of the diagonal terms, the Jacobian determinant is therefore tractable and can be efficiently computed. Real valued non-volume (Real NVP) transformations [10] extend the work in [9] to create a set of powerful, stably invertible and learnable transformations. This method performs efficient and exact log density estimation of data points \( x \). GLOW [11] suggests using invertible \( 1 \times 1 \) convolutions to replace fixed permutations in [10] by learned \( 1 \times 1 \) convolutions, while remaining efficient. Moreover, they suggest using an actnorm layer instead of the usual batch normalization. In this work we use RealNVP to obtain efficient density estimation of our background features.

The benefits of normalizing flow are: (i) it can learn much more complex distributions, and (ii) the only information that must be saved are the weights of the flow model, which requires very low memory. However, extracting features from deeper layers of the expert model results in higher dimensional descriptors, which makes the training of the density estimation harder and less stable. Unstable training can be easily detected by using a small validation set: it becomes unstable when the likelihood of the validation set starts to diverge from the one of the training set. To alleviate training difficulties, one must use a batch size large enough to contain diverse background features.

Flow Ensemble:
We perform density estimation at each individual layer of our expert network’s encoder. A flow ensemble consists of combining the results from separate layers, similar to [30]. However, the individual negative log-likelihood (NLL) estimates cannot be aggregated because the different background features distributions have varying dispersion and dimensions. Densities at different layers thus have different scales. Similar to [12], we first center the NLL at layer \( l \) around the average NLL of the training features for that layer: \( \bar{N}(z_l) = \bar{N}(z_l) - \bar{L}(z_l) \). In the ideal case of a multivariate Gaussian, \( \bar{N} \) corresponds to the Mahalanobis distance used in [30]. Using a small validation set, we estimate the mean and standard deviation to normalize \( \bar{N} \) such that the NLL of individual layers can be compared. Following [12], we experiment with three strategies: (i) A pixel is detected as foreground only if all layers agree that it has low log likelihood (high NLL), thus having a high minimum NLL. (ii) A pixel is detected as foreground if it has a low log likelihood on at least one layer, thus having a high maximum NLL. (iii) Using a small set of new labeled images, we fit a logistic regression to capture the interaction between the layers and use it to improve the individual predictions.

4 Experiments and Results

Dataset:
We use the NYU Depth v2 dataset, which contains 1449 densely labeled images of indoor scenes. We sort the dataset to select images containing roughly as much background as foreground, retaining 580 images (493 for training, 87 for testing) with a balanced number of foreground and background pixels. We augment the data with flipping, rescaling, brightness and contrast changes. This dataset
however only contains 464 different indoor scenes: a scene thus appears several times from different viewpoints, and could therefore be found in both our train and test set since they are randomly split. We therefore also created a dataset of 70 labeled images that consists of indoor images drawn from datasets different from NYU, which also aims to better capture the high variability encountered in real life scenes. It includes: pictures taken with a smartphone, images downloaded online, black-and-white fish-eye images from construction sites, synthetic images, as well as collages (empty room images that we edited to add objects). It contains approximately 80% background pixels. We use 45 images to create the validation set on which we will evaluate the performance. The 25 others are used as a fitting dataset to fit the logistic regression of the flow ensemble.

Evaluation metrics:
To evaluate our results, we use several common metrics for segmentation. A pixel is “true positive” if it is correctly classified as foreground. The True Positive Rate (TPR or recall) is the fraction of foreground pixels that are successfully labeled. As our method is motivated by safety, we value having a low number of misclassified foreground pixels. We thus compute the False Positive Rate (FPR) at 95% TPR: our first constraint is to ensure a high TPR (95%) and then we report the corresponding FPR value. We also employ the Area Under the Receiver Operating Characteristic Curve (AUROC), the average recall and the average precision, which are threshold-independent performance evaluation metrics. The AUROC can be interpreted as the probability that a positive example has a greater detector score/value than a negative example. Consequently, a random positive example detector corresponds to a 0.50 AUROC, and a perfect classifier to a 1.00 AUROC [31]. The recall score shows our ability to detect objects: the higher it is, the more foreground objects we can detect. The average precision score shows the overall segmentation quality.

4.1 Results on the NYU test set
In this section, we have a closer look at how our results on the NYU test set are influenced by two main factors: the layers of the FCN from which the background features are extracted (layers 3, 4, 5, 6, or a combination of all these layers), and the weights used for the FCN’s encoder (NYU segmentation or ImageNet). We qualitatively show these results in figure 2, and quantitatively in table 1. Figure 3 furthermore shows the ROC curve obtained on the NYU test set (solid lines).

| FPR_{95\%TPR} (%) | Average Recall (%) | Average Precision (%) | Area under ROC |
|-------------------|--------------------|-----------------------|--------------|
|                  | NYU segm. | ImageNet | NYU segm. | ImageNet | NYU segm. | ImageNet | NYU segm. | ImageNet |
| FCN Segm.        | -         | -        | 45.2      | 65.1     | 37.4      | 21.3     | 0.87      | 0.75     |
| layer 6          | 72.1      | 73.8     | 8.0      | 18.3     | 56.0      | 64.4     | 0.63      | 0.71     |
| layer 5          | 85.5      | 71.6     | 1.6      | 19.8     | 49.6      | 67.8     | 0.54      | 0.73     |
| layer 4          | 88.0      | 71.5     | 5.8      | 19.8     | 53.9      | 67.8     | 0.60      | 0.73     |
| layer 3          | 90.0      | 86.5     | 4.5      | 13.1     | 52.6      | 61.1     | 0.54      | 0.65     |
| kNN              | -         | -        | 45.5      | 76.6     | 38.8      | 17.9     | 0.88      | 0.70     |
| layer 6          | -         | -        | 47.5      | 76.9     | 39.8      | 17.7     | 0.87      | 0.79     |
| layer 5          | -         | -        | 49.6      | 78.8     | 36.6      | 19.1     | 0.84      | 0.72     |
| layer 4          | -         | -        | 62.3      | 80.6     | 27.1      | 17.9     | 0.78      | 0.69     |
| layer 3          | -         | -        | 64.1      | 87.7     | 22.2      | 17.1     | 0.76      | 0.69     |
| Normalizing Flow (our approach) | regression (fit on fitting set) | max NLL | 52.6      | 76.6     | 37.8      | 18.0     | 0.85      | 0.70     |
| layer 6          | -         | -        | 53.4      | 73.3     | 37.3      | 18.0     | 0.87      | 0.70     |
| layer 5          | -         | -        | 63.8      | 80.7     | 20.8      | 18.5     | 0.74      | 0.69     |
| layer 4          | -         | -        | 64.1      | 87.7     | 22.2      | 17.1     | 0.76      | 0.69     |
| layer 3          | -         | -        | 64.1      | 87.7     | 22.2      | 17.1     | 0.76      | 0.69     |

Table 1: Evaluations computed on the NYU test set. Bold values indicate the best performance obtained by each approach (segmentation, kNN, normalizing flow with individual layers, flow ensemble). Blue values indicate the best performance overall. To get the segmentation and layer 6 on ImageNet, we imported the ImageNet weights into the encoder and trained only the decoder.

*Density could not be stably trained on layer 5 for ImageNet, and therefore the layer combination only includes layers 3, 4, and 6.*
4.2 Generalization on the validation set

We use our validation set to show how well our method generalizes to novel objects. Figure 4 shows a few examples from the validation set where the FCN fails to segment objects outside of the training set, while our method does not suffer from these new objects. Table 2 quantitatively shows that our method outperforms FCN and kNN on the validation set. Figure 3 furthermore shows the ROC curve obtained (dotted lines).

| Method               | FPR @ 95% TPR (%) | Average Recall (%) | Average Precision (%) | Area under ROC |
|----------------------|-------------------|--------------------|-----------------------|----------------|
| FCN Segm. - -        | 80.6 (+35.4)      | 27.0 (+10.4)       | 40.8 (+40.93)         | 0.77 (+0.10)   |
| kNN layer 4 -        | 63.5 (-8.0)       | 24.1 (+1.3)        | 41.8 (+26.0)          | 0.76 (+0.03)   |
| Normalizing Flow -   | 56.1 (+10.6)      | 35.8 (+7.13)       | 59.2 (+27.6)          | 0.84 (+0.04)   |
| (our approach) 5+6   | 62.3 (+14.3)      | 35.9 (-3.9)        | 57.3 (-30.6)          | 0.83 (-0.06)   |

Table 2: Evaluations computed on the validation set. Only the weights and layers giving the best results on the test set are shown here: FCN segmentation (NYU segmentation weights), kNN layer 4 (ImageNet weights), normalizing flow on layers 3+4+5+6 (NYU segmentation weights). Values in bracket show the difference between validation and test set results.

Figure 3: ROC curve on the test (solid line) and validation (dotted line) sets. Only the weights and layers giving the best results on the test set are shown here: FCN segmentation (NYU segmentation weights), normalizing flow regression on layers 3+4+5+6 (NYU segmentation weights), kNN layer 4 (ImageNet weights).

Figure 4: Example results on the validation set (red dotted circles were added to highlight FCN failures). (a) & (b) Advertisement images where part of the chair / textile roll is missed by the FCN. (c) & (d) Picture from Google Image where we add a human and a fridge (objects not part of our training set): this shows that the FCN is unreliable on novel elements while density estimation techniques can find these objects. (e) Greyscale fish-eye image from a construction site: this image is so different from NYU that the FCN is very imprecise. (f) Smartphone picture of a living room: several elements are missed by the FCN.

5 Discussion

We first have a look at the performances of kNN. As shown in table 2, it has the benefit of performing similarly on the test and validation sets (even slightly improving on the validation). However, we notice in tables 1 and 2 that it is a poor high dimensional density estimation method compared to normalizing flow as its performance is lower on all evaluated metrics. This shows that kNN cannot model the complex high dimensional probability distribution of background features. We therefore focus the rest of this discussion on our flow-based approach.

Using ImageNet weights allows us to avoid training the expert network. However, as seen in table 1, the results are much poorer than with the NYU segmentation weights. This could come from extracted features not being relevant for our task: [32] shows that ImageNet-trained CNNs are strongly
biased towards recognising textures rather than shapes. This is problematic for our task, since most man-made objects (tables, chairs, sofas, shelves etc.) found in indoor scenes have a rather planar surface with a texture difficult to differentiate from walls or floors. Although this could explain lower performance, the biggest drawback comes from instability when training the normalizing flow on ImageNet weights. The main difference between the NYU segmentation and the ImageNet weights is that the latter does not use batch normalization. This made training of the density estimation much harder so we had to use early stopping when the log likelihood of the NYU validation started to decrease. Our network could thus not entirely model the distribution of background features, which explains the poor results on ImageNet. Indeed, as seen in table 1, on ImageNet the flow-based method gives similar results to kNN, which we know is a poor density estimation approach in this setting. We conclude that supervised learning of the expert network for the desired task improves the results and batch normalization increases the stability of the flow-based density estimation. Therefore, only the results obtained with the NYU segmentation weights will be addressed in the rest of this discussion.

We observe in table 1 that deeper layers yield better results when using the NYU segmentation weights for the encoder. This is expected as features get more specific and are thus more valuable to distinguish foreground from background. In particular, the results of either layer 5 or 6 outperform the FCN segmentation on all metrics, except on the FPR95%TPR. By using a weighted average of the probability results at all layers, we further improve all the metrics and reach almost the same FPR95%TPR as FCN segmentation. The weights are learned by fitting a logistic regression using a small fitting set. Note that results on the test set show that using the training set to fit the regression is slightly better than using an external fitting dataset (see table 1), but the results on the validation set show greater benefits of using the fitting set (see table 2). When deployed in real life, our segmentation method will encounter scenes completely different to the ones seen in the train or test set of NYU. We therefore recommend using an external fitting set for the logistic regression, as it gives us better results on images different from the NYU dataset.

Finally, using the validation set, we show that our approach generalizes better to new images and outperforms both FCN and kNN on all metrics with a large margin, as shown in table 2. Our method is superior on new images because its performance is less affected by novel objects than the FCN segmentation. This can also be seen on the ROC curves in figure 3. Finally, we also show in figure 4 how the performance varies with regards to distortion of images, color changes, camera type, photo collages, and variety of foreground objects.

A limitation of our method is that, similarly to the FCN segmentation, planar and texture-less surfaces are often mistakenly labeled as background, with high certainty. Another limitation is that background not found in the training set will be labeled as foreground. For example, some types of floor (e.g. parquet) are often thought to be less likely to be background than walls. This limitation however emphasizes the strength of our method: given data that has no support in the training set, we recognize it as unlikely. Autonomous agents using our segmentation method will thus be aware of the uncertainty in data they were not trained on.

6 Conclusion

We presented a novel approach to segment foreground from background in indoor environments, with high reliability against the variability of indoor scenes. Unlike any existing works, we learn the probability distribution of background features using flow-based methods in order to distinguish foreground objects. The combination of several layers further increases the performance of our approach and yields the best results. We demonstrated that our method outperforms classical FCN segmentation on the NYU test set. More importantly, the advantage of our method clearly increases over FCN when evaluating the performance on a new validation dataset. This is critical in order to deploy our work for real life applications.

Our results are promising to increase the reliability in finding the background in indoor scenes. This has potential impact on a variety of robotic tasks, i.e., novelty detection in indoor scenes, obstacle avoidance by recognizing arbitrary objects, or long-term localization by reliably segmenting building structure from potentially dynamic objects. We see all of these as exciting directions for future research.
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7 Additional Material

7.1 Motivation

We use t-SNE (t-Distributed Stochastic Neighbor Embedding) to show how background and foreground features (extracted from the expert model) can be clustered in 2 dimensions. Figure 5 shows the results obtained at various layers. The separation between foreground and background features becomes more prominent with deeper layers, which has given us the intuition that the features of deeper layers are more useful to segment foreground from background. This has been confirmed in our work.

![Layer 3](image1.png) ![Layer 4](image2.png) ![Layer 5](image3.png)

*Figure 5: t-SNE results performed at various layers of the FCN. Blue represents background features, and red foreground features.*

7.2 Background Classes in the NYU dataset

The images from the NYU dataset are densely labeled, with a total of 894 individual labels. We sorted them in order to generate the binary foreground-background masks. The following labels were mapped to background:

- ceiling, floor, wall, air vent, cork board, air duct, pipe, whiteboard, ladder, window, projector screen, air conditioner, blinds, room divider, curtain, electrical outlet, heater, circuit breaker, rug, towel, rod, floor mat, stairs, blackboard, radiator, light switch, fire alarm, classroom board, poster board, board, chart, glass panel, banister, photo, wooden planks, window cover, stones, door way, glass, door frame, door window reflection, knob, door facing trim reflection, door reflection, light switch reflection, brick, wooden plank, garage door, lamp shade, reflection of window shutters, floor trim, american flag.

7.3 Additional Details about Normalizing Flow

In this work we stack 32 steps, each one composed of an affine coupling layer, a batch normalization layer, and a fixed random permutation. As recommended by [11] we initialize the weights of the coupling layers such that they initially perform identity transformations. Although normalizing flow is a nice tool to model complex density distributions, its implementation can be difficult due to instability in training.

First of all, similarly as in [12] we found that it is critical to extract features before ReLU activation, as some dimensions might be negative for all training points. Having a dimension constantly at the same value (zero) makes the training highly unstable. Secondly, the bigger the dimensions of the features, the more difficult it gets to have stable training. The biggest issue with normalizing flow networks is that they can converge towards a high dimensional region where only a few training examples are located and never escape from this local minimum. Being stuck in a local minima leads to training instability because the network reduces the Negative Log-Likelihood (NLL) by simply converging more towards the few examples of the training set, until the probability of all the other data points is so low that the NLL exceeds the computers 64 bits representation (even in log space). We suggest four ways to alleviate this:

- **Large Batch Size:** By using a large batch size, the batch represents better the distribution of background features and the network is thus less likely to converge only to a few points in the training set.
• **Low learning rate:** Using a low learning rate increases the training time but helps avoiding the convergence to local minima from which the network could not recover. A local minima is typically an estimated density distribution that gives a very high probability to a few training examples in the training set and a probability close to zero for the rest.

• **Early stopping:** Using a small validation set, we can identify when the network becomes unstable. Instability of training is characterized by a large and sudden increase of the validation NLL. Overfitting is detected when the NLL on the validation set stops decreasing, although the NLL on the training set is decreasing.

• **Low amount of chained bijectors:** The best method to guarantee training stability is to limit the complexity of the flow. By chaining less bijectors, we prevent the flow from learning too complex distributions, which stabilizes training. This however restricts the density estimation capabilities of our network which is then not able to learn highly complex distributions of background features, negatively affecting our performance.

Training our normalizing flow with 32 chained bijectors was much easier for the NYU weights than the ImageNet weights. In the paper, we reported no results for layer 5 of ImageNet, although it would be possible to train a flow with less chained bijectors for this layer (for instance, 5 bijectors). However, reducing the number of bijectors comes at the cost of a poorer estimation of high dimensional probability distributions, yielding bad results. We concluded that the training difficulties with ImageNet were mostly due to the absence of batch normalization and not to the quality of the features: table 3 shows similar performance between the NYU and ImageNet on the validation set.

### 7.4 Additional Results

#### 7.4.1 Quantitative Results

In the paper, we present a complete table of results for the test set and a reduced table for the validation set. Table 3 contains all the results obtained on the validation set.

|                | FPR 95% (\%) | Average Recall (%) | Average Precision (%) | Area under ROC |
|----------------|--------------|--------------------|-----------------------|---------------|
|                | NYU segm.   | Image NET         | NYU segm.             | Image NET     | NYU segm.   | Image NET     | NYU segm.   | Image NET     |
| **FCN Segm.**  |              |                    |                       |               |              |               |              |               |
| layer 5        | -            | 80.6               | 71.7                  | 27.0          | 31.9        | 40.8          | 30.2        | 0.77          | 0.80          |
| **kNN**        |              |                    |                       |               |              |               |              |               |
| layer 5        | -            | 65.7               | 64.4                  | 9.2           | 18.0        | 31.8          | 29.3        | 0.70          | 0.75          |
| layer 6        | -            | 75.9               | 59.8                  | 7.3           | 27.0        | 29.2          | 47.8        | 0.67          | 0.80          |
| **Normalizing Flow (our approach)** | | | | | | | | |
| 3+4+5+6\*     | regression (fit on fitting set) | 56.1 | 51.8 | 37.8 | 36.6 | 59.2 | 57.0 | 0.84 | 0.84 |
| max NLL       | -            | 62.3               | 51.9                  | 35.9          | 36.4        | 57.3          | 56.6        | 0.83          | 0.84          |
| min NLL       | -            | 59.3               | 50.8                  | 29.9          | 37.1        | 50.2          | 57.4        | 0.80          | 0.84          |
| layer 5        | -            | 63.4               | 55.9                  | 30.7          | 35.8        | 51.4          | 56.1        | 0.80          | 0.83          |
| layer 6        | -            | 65.6               | 51.6                  | 31.5          | 36.7        | 51.8          | 37.1        | 0.80          | 0.84          |
| layer 4        | -            | 69.7               | 55.7                  | 29.7          | -           | 50.8          | -           | 0.80          | -             |
| layer 3        | -            | 59.7               | 55.7                  | 17.6          | 36.4        | 37.8          | 56.7        | 0.76          | 0.83          |
| layer 5        | -            | 61.5               | 65.5                  | 22.8          | 32.5        | 48.0          | 52.7        | 0.79          | 0.81          |

*Density could not be stably trained on layer 5 for ImageNet, and therefore the layer combination only includes layers 3, 4, and 6.

Table 3: Evaluations computed on the validation set. Bold values indicate the best performance obtained by each approach (segmentation, kNN, normalizing flow with individual layers, flow ensemble). Blue values indicate the best performance overall. To get the segmentation and layer 6 on ImageNet, we imported the ImageNet weights into the encoder and trained only the decoder.

The Receiver Operating Characteristic (ROC) and Precision-Recall (PR) curves for all layers (3, 4, 5, 6, 3+4+5+6) and training types (NYU segmentation, ImageNet) are displayed in figure 7. The legends are indicated in figure 6.

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2Weights found online at: https://www.cs.toronto.edu/~frossard/post/vgg16/
7.4.2 Qualitative Results

Figures 8 to 17 display the results of our approach on images from the validation dataset. We show that it generalizes very well to all types of images. The first column contains the input image and the FCN probability (softmax confidence) using the weights learnt with the NYU segmentation (\textit{FCN prob}) and with ImageNet (\textit{ImageNet prob}). The second and third columns contain the density obtained using normalizing flow for all the weights (NYU segmentation, ImageNet) and all the layers (layers 3, 4, 5, 6). The last column contains the results for the combination of layers 3, 4, 5 and 6 (minimum and maximum NLL as well as the regression fit on an external dataset, coined fitting dataset). Note that as explained in the paper, there is no visualisation for ImageNet on layer 5 as the training was not stable.

Figure 8: Smartphone picture of an open study space.  
Figure 9: Smartphone picture of a shelf.
Figure 10: Image of a bathroom floor with grey t-shirts on the ground.

Figure 11: Computer-generated image of a salt and pepper mill (Google images).

Figure 12: Smartphone picture of a corridor in a lab.

Figure 13: Room with a fridge (Google image).

Figure 14: Black-and-white image from a construction site.

Figure 15: Part of a red chair in front of a red wall (Google image).
7.4.3 Limitations

Figures 18 and 19 illustrate the limitations of our method. In figure 18, the bed should be entirely classified as foreground. However, the white towel on the bed sheets is labeled as background with high probability. We notice that covering objects with a white towel makes our approach fail, probably because white texture-less areas are a strong background characteristic. Additionally, in the bottom right corner of image 19, the furniture is mistakenly labeled as background. This phenomenon has been seen repeatedly: planar and texture-less surfaces are often mistakenly labeled as background, with high certainty. However, we see that the regression helped a lot with this phenomenon (top-right image of figure 19). This kind of improvement explains the superiority of the layer combination’s performance.

Another limitation is that our dataset contains less floor than walls or ceiling. This explains why the floor is often thought to be less likely to be background than walls. Wooden floors have proven to be particular difficult for our model. This limitation however shows the strength of our method: given data that has no support in the training set, our method recognises it at being unlikely. Autonomous agents using our segmentation will thus never venture in spaces for which they have not been trained.