Supplementary Materials for ‘Net2Vec: Quantifying and Explaining how Concepts are Encoded by Filters in Deep Neural Networks’

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1. Classification Training Details

For each concept c’, the classification concept weights $\mathbf{w}$ are learned using stochastic gradient descent with momentum (learning rate 10^{-1}, momentum $\gamma = 0.9$, batch size 64, 30 epochs) to minimize the following binary cross entropy loss:

$$\mathcal{L}_2 = \mathop{\mathbb{E}}_{\mathbf{x}\sim X_{s,c}} \big[y(\mathbf{x}) \log f(\mathbf{x}; \mathbf{w}, b) + (1 - y(\mathbf{x})) \log(1 - f(\mathbf{x}; \mathbf{w}, b))\big] \quad (1)$$

where the label $y(\mathbf{x}) = +1$ if $\mathbf{x}$ contains c and $y(\mathbf{x}) = 0$ otherwise. Here the expectation symbol is used to indicate the fact that the set $X_{s,c}$ is sampled in the balanced manner just explained. We also reduce the learning rate to 10^{-2} halfway through training after epoch 15. To evaluate performance, we calculate the classification accuracy over a balanced validation set.

2. Quantifying the Filter-Concept Overlap

2.1. Are Filters Sufficient Statistics for Concepts?

Figure 1 shows the mean classification accuracy for different AlexNet layers when using the top K filters for the classification task. This figure demonstrates that discriminative ability improves with layer depth and that, on average, saturation in performance occurs similarly for different layers (i.e., around $F \in [40, 50]$).

Figure 2 shows segmentation and classification results for individual VOC Pascal concepts. Generally, for both tasks, performance improves with layer depth. Low segmentation performance for bottle and chair can be explained by the fact that images for those two concept classes come from more than one original dataset source (i.e., BRODEN images in those concept classes are not just VOC Pascal images).

Figure 3 and Figure 4 show segmentation and classification results respectively for the 20 VOC Pascal classes when varying the number of top filters F with which to learn concept. From the VOC Pascal segmentation results, three patterns arise: First, for some concepts, i.e., 'airplane' and 'sofa', performance improves as F increases. Second, for others, i.e., 'bird' and 'cow', performance peaks for some small F and then decreases slightly as F increase (or greatly, in the case of 'tv monitor'). This is likely because additional filters may not be necessary for segmenting certain concepts and may contribute to over-fitting. Third, for a few concepts, i.e., 'bottle' and 'chair', performance is quite low and decreases after $F = 1$. This is likely due to over-fitting and the fact that for these concepts, the images come from more than one original dataset.

Aside: Top F=1 Filter vs. Best Filter for Segmentation. For segmentation experiments in which we learn weights for the top F filters, the IoU_{set} score when $F = 1$ may be different than when using our modified version of NetDissect's best single filter approach. This occurs for two reasons: First, in a few cases, a different top $F = 1$ filter, compared to that selected as the best filter, is selected (this is because the top $F = 1$ filter is chosen by being the filter with the largest magnitude learned weight). Second, in the top $K = 1$ setting, a scalar weight is learned; this is then used to weight the top $F = 1$ filter's activations. In the NetDissect-style of using the best filter, there's no scalar weight that's learned, a filter's activations are simply thresholded. This is why the IoU_{set} scores for $F = 1$ in Figure 3 differ from those for the best filter in Figure 2.

Figures 5 and 6 show the difference between the IoU_{set} scores when using learned weights vs. the best filter on the segmentation and classification tasks respectively. As you can see, for the most part, our weighted, multi-filter method improves upon methods in which only a single filter is used and our improvements can be quite large (i.e., up to $0.4\ \text{IoU}_{\text{set}}$ and 0.5 accuracy improvements). However, for a non-negligible amount of concepts (in orange), our method performs worse. We analyze this in the main text and provide supporting figures in the next section.

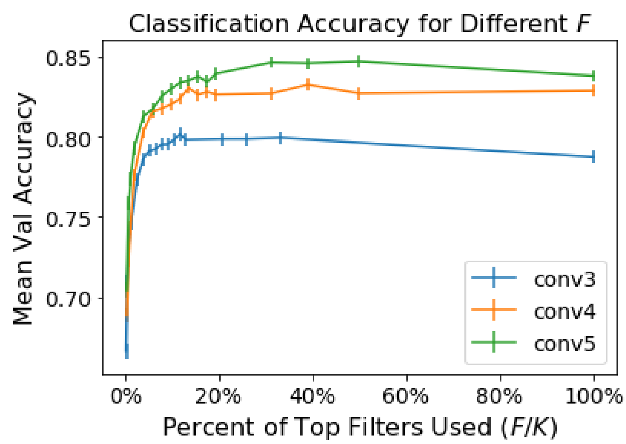


Figure 1. Mean Classification Accuracy over 1189 classification concepts for each layer.

2.1.1 Failure Cases

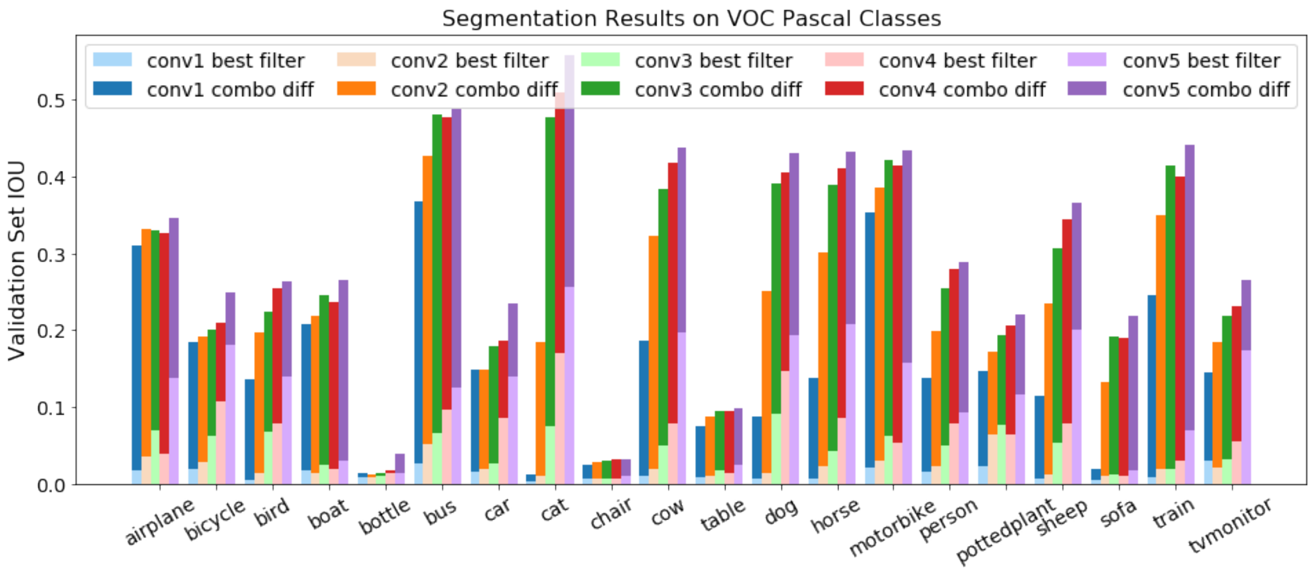
Figure 7 shows that most concepts for which our method performs worse for segmentation are quite small, i.e. on average fill up around 1% of an image. Because spatial resolution decreases as layer depth increases, i.e., AlexNet conv5 activations have a spatial resolution of 13×13; this makes optimizing a concept size-weighted loss (main text eq. (4)), where $1 - \alpha$ is the mean fraction of an image) difficult and unstable. Furthermore, for a few failure cases, there are simply too few training examples for a concept (i.e., orange points spanning the bottom boundaries of the plots), which leads to over-fitting. Figure 8 shows that small concept datasets also explains failure cases for the classification task, where most failure cases have less than 100 training examples.

2.2. Are Filters Shared between Concepts?

Table 1 shows the number of filters in each AlexNet layer as well as the average number of concepts per filter if concepts were uniformly distributed across filters (for comparison with main fig. 5).

For the following 13 conv5 filters, thresholding activations using the best single filter yielded $\text{IoU}_{\text{set}} > 0.15$ on both training and validation sets and for multiple concepts (validation IoU_{set} scores in parentheses):

1. unit 15: dotted (0.3710), perforated (0.2505), polka-dotted (0.4716), studded (0.1956), honeycombed (0.4169), chequered (0.3171)



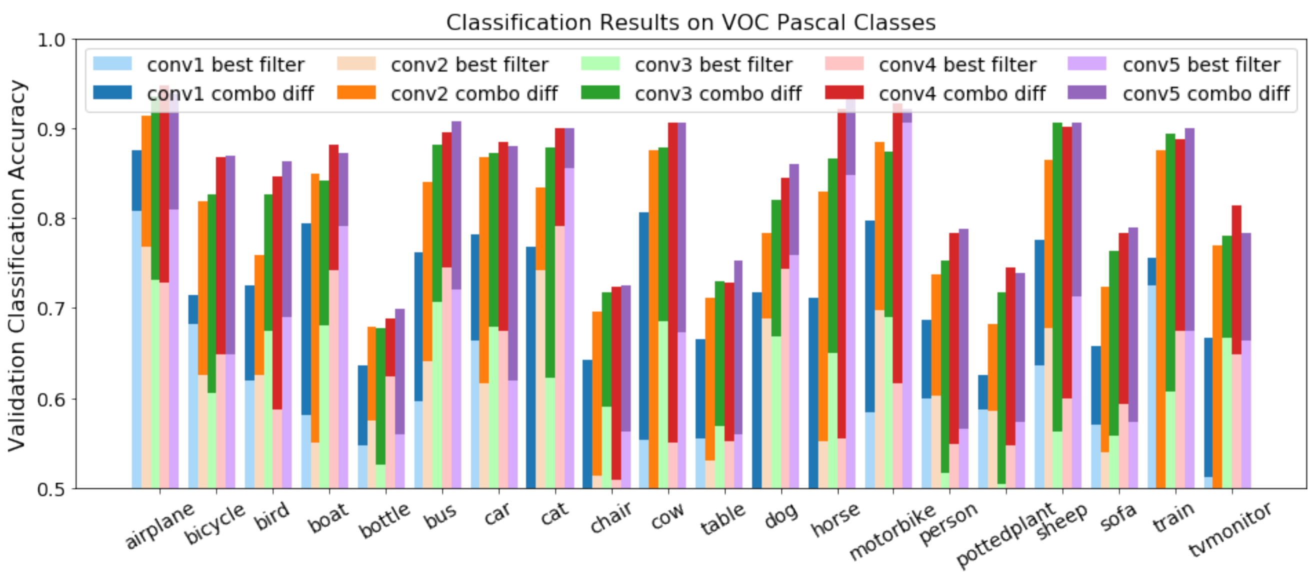


Figure 2. Results for the 20 VOC Pascal concepts on the segmentation (top) and classification (bottom) tasks. Light colored bars represent performance using the best filter while bold colored bars represent the additional improvement in performance using the learned weighted combination of filters. For classification, the following best filter cases fell below the 50% threshold (accuracies are given in parentheses): conv1 — cat (0.49), chair (0.49), dog (0.48), horse (0.47), cow (0.48), train (0.44); conv2 — tvmonitor (0.50).

	conv1	**conv2**	**conv3**	**conv4**	**conv5**
# of filters	64	192	384	256	256
avg. concepts/filter (seg./class.)	10.7/18.6	3.6/6.2	1.8/3.1	2.7/4.6	2.7/4.6

Table 1. The number of filters in each AlexNet conv layer and the average number of concepts per filter (i.e., # of concepts [682 for segmentation and 1189 for classification] / # of filters).

2. unit 30: horse (0.1775), cow (0.1576), elephant (0.3050)
3. unit 32: pool table (0.2570), swimming pool (0.3088), aquarium (0.2629)
4. unit 55: washer (0.1762), tunnel (0.2126)
5. unit 66: horse (0.2088), sheep (0.2126), cow (0.1968)
6. unit 109: dog (0.1877), cat (0.1729)
7. unit 111: screen (0.1671), tvmonitor (0.1736), monitor (0.1545), silver screen (0.2389)
8. unit 114: dotted (0.2740), polka-dotted (0.2679)
9. unit 130: dog (0.1531), cat (0.2561)
10. unit 176: dog (0.1939), cat (0.1694), sheep (0.2008)

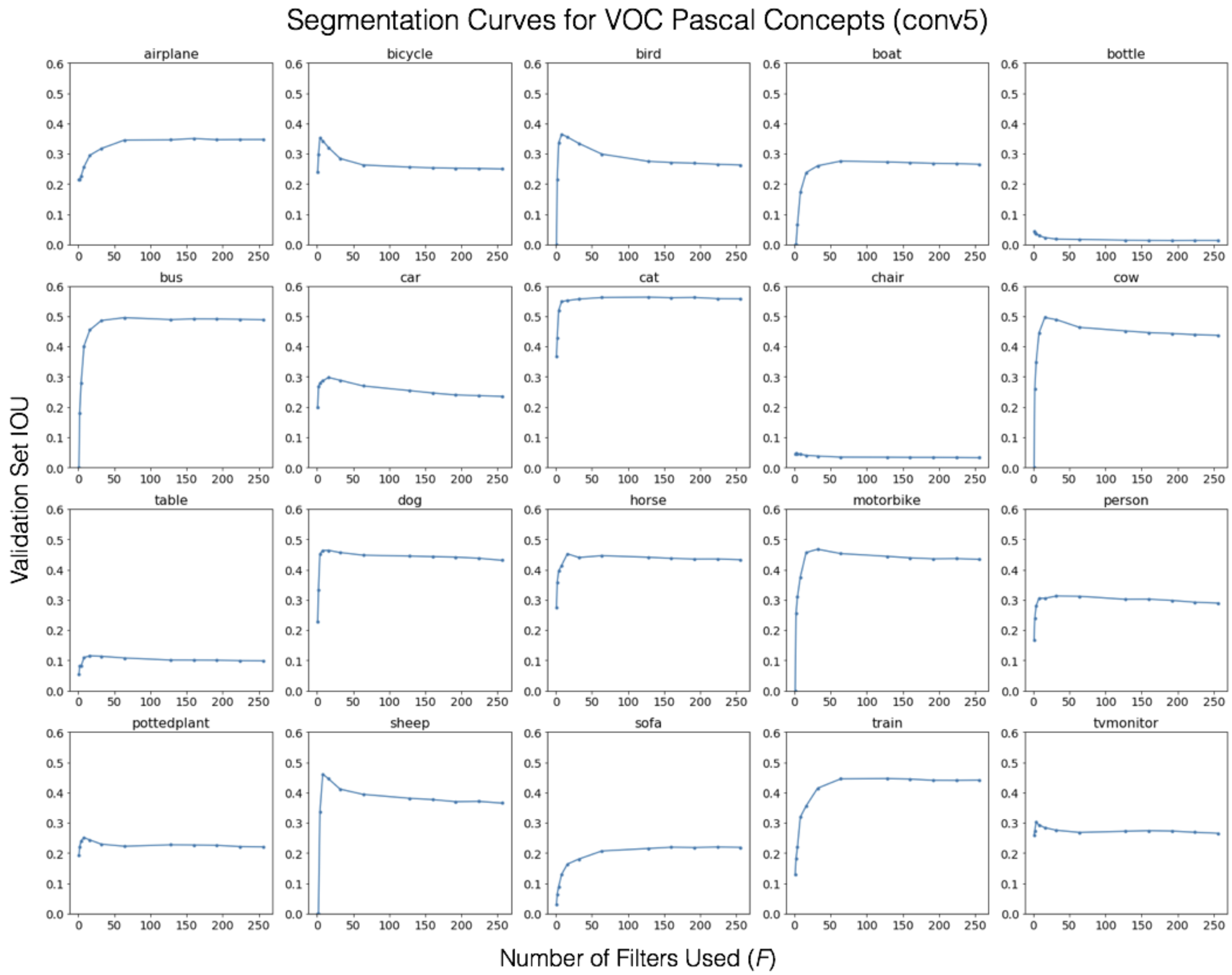


Figure 3. Segmentation results for the 20 VOC Pascal concepts when learning weights to combine conv5 activations from a variable number of top filters F.

11. unit 206: aqueduct (0.1515), viaduct (0.1734)
12. unit 248: bicycle (0.1801), swirly (0.1842), paisley (0.1510), steering wheel (0.1531), labyrinth (0.2816)
13. unit 255: banded (0.1995), striped (0.3436), zigzagged (0.1726)

Figure 9 visualizes the examples with the best IoU_{ind} scores of concepts associated to units 32, 55, 130, 176, and 248. In the case of filter 428 (top row), it appears that the filter is firing on circular, swirly patterns that do not have an obvious human-labelled concept associated to it. Main fig. 4 visualizes the top four examples for every concept associated to unit 66, which seems to be firing for an pastoral animal's torso. This suggests that individual filters might be firing for cohesive concepts that may not have clear human labels.

In the main fig. 4, a number of filters were identified as being selected as the best filter for 20 or 30 or more concepts for the segmentation and classification tasks respectively. To see comprehensive lists of these filters and the concepts for which they were supposedly selective for, see Appendix, Section A.

2.3. More Architectures, Datasets, and Tasks

Figure 10 shows results when probing different architectures, datasets, and tasks using the Net Dissect approach of reporting results (i.e., thresholding set IoU scores). It shows how GoogLeNet trained on Places revealed strong single filter scene detectors (right); however, scenes and textures were excluded in our experiments due to the lack of segmentation annotations available for them.

GoogLeNet vs. VGG16 Figure 11 shows that GoogLeNet layers inception4c and inception4e (14×14)

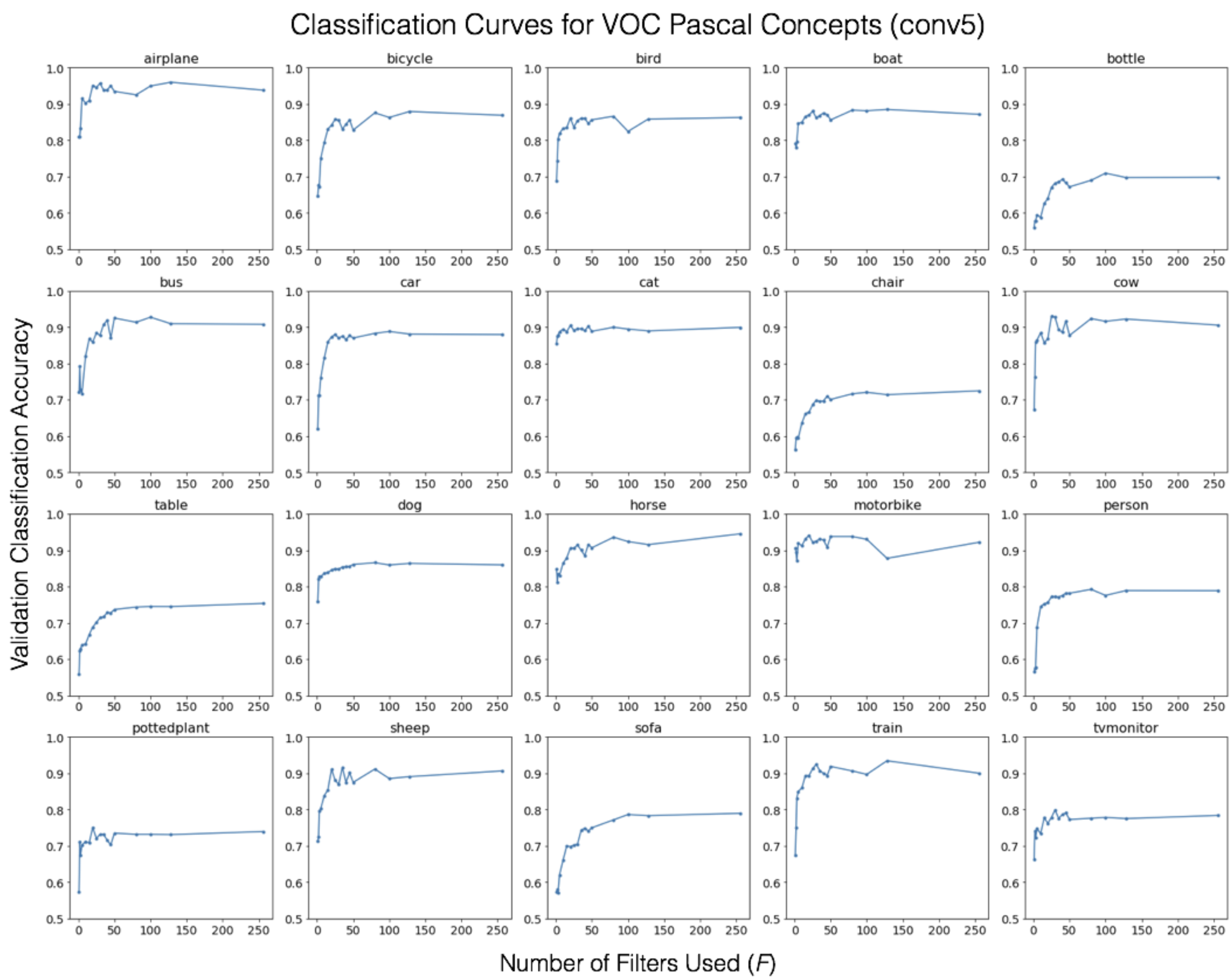


Figure 4. Classification results for the 20 VOC Pascal concepts when learning weights to combine conv5 activations from a variable number of top filters F.

outperform later convolutional layers inception5a and inception5b (7×7) as well as VGG16 later convolutional layers (14×14).

Fully-Connected Layers Figure 12 shows classification results for AlexNet trained on ImageNet for all convolutional and fully connected layers. fc6-7 likely drop in performance because they contain more hidden units (4096) that are more distributed, harder to optimize over, and are not average pooled over in the probe task like activations from convolutional layers.

3. Interpretability

3.1. Visualizing Non-Maximal Examples

Figures 13 and 14 show the maximally-activating examples for the following concepts: 'house', 'dog', 'plant', 'airplane', and 'train'. Figure 14 demonstrates that the images that were most maximally aligned to 'train's best filter were not 'train' images (top row, first four examples). Figure 15 shows the every decile visualization for the 'house', 'plant', and 'train' concepts (analogous to main fig. 8).

Maximally-Aligned to Concept Weights. Alignment with a given filter is quantified by saving each filter's maximum activation across spatial locations for each example. This allows for the sorting of examples based on alignment to filters and is how maximally-activating images are selected in this work as well as in NetDissect. To compute alignment with a learned concept weights vector for segmentation, an example's activation map is thresholded by $\tau = 0.005$ activation's quantile T_k for all filters k. The threshold activations are linearly combined and weighted

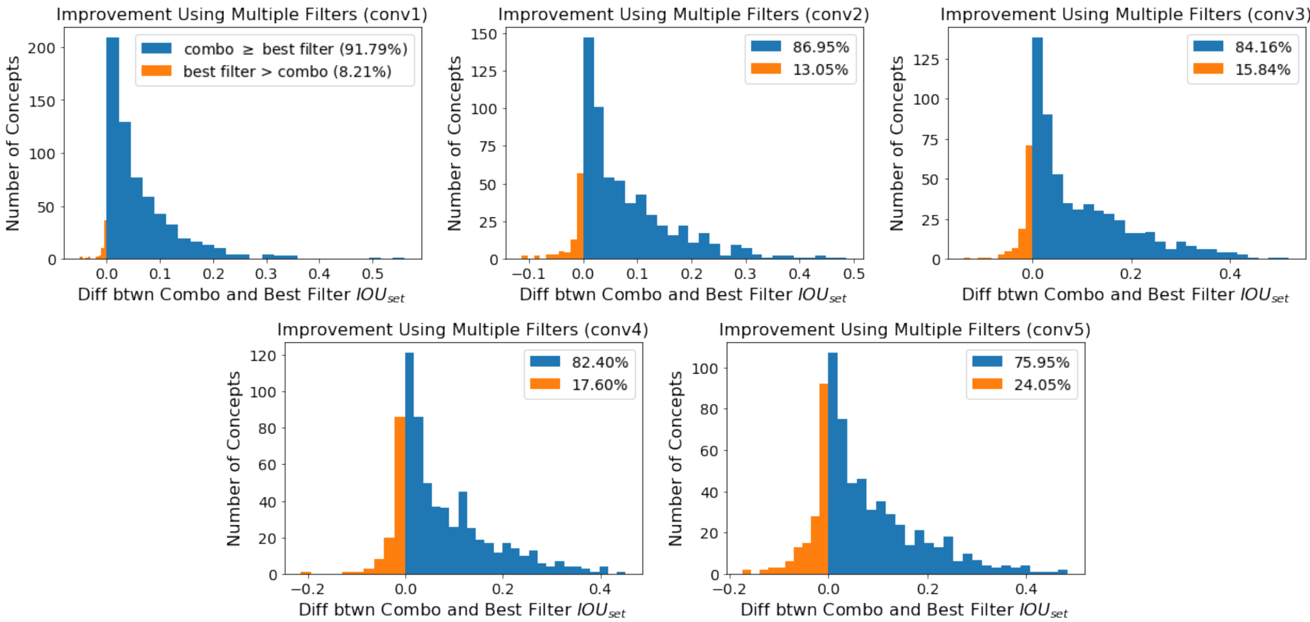


Figure 5. Histogram of difference between the IoU_{set} scores when using our learned weights versus the best filter on the training set for 682 concepts with segmentation annotations (percentages reflect the portion of concepts for which our combined method is better or worse).

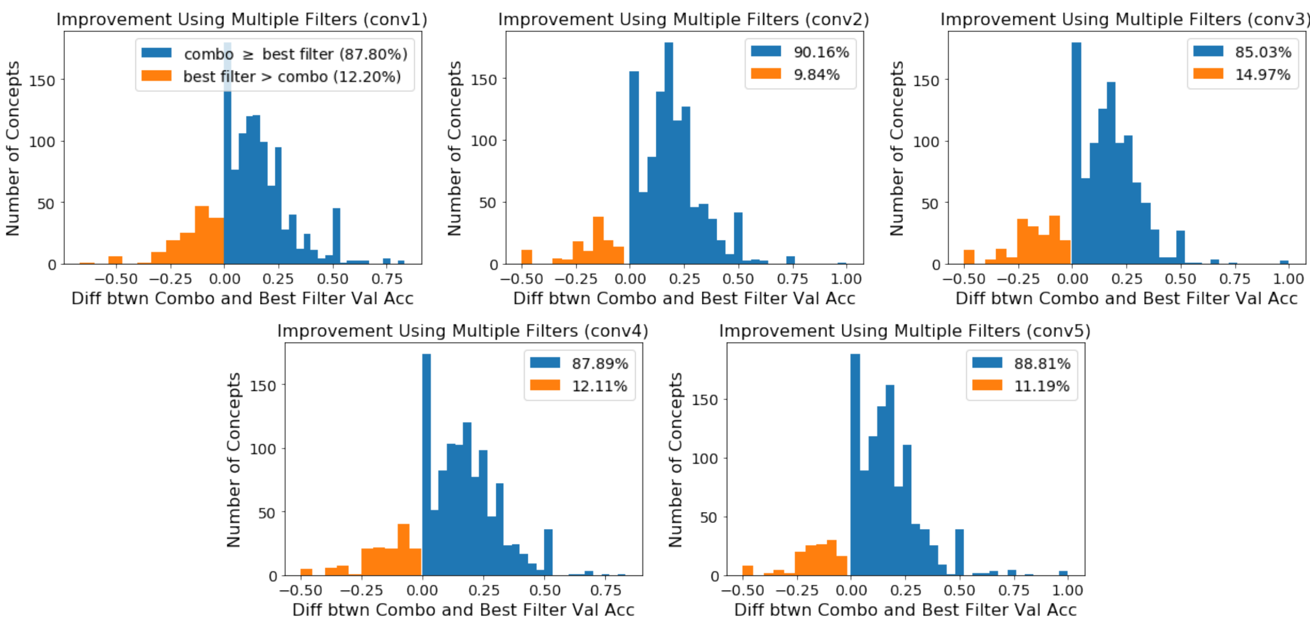


Figure 6. Histogram of difference between the classification accuracy on validation sets when using our learned weights versus the best filter on the training set for 1189 concepts (percentages reflect the portion of concepts for which our combined method is better or worse).

by the concept weights vector; the maximum value across spatial locations of this linearly combined map is used to measure alignment with a concept vector.

3.2. Explanatory Power via Concept Embeddings

To explore how concept embeddings related to one another, we performed K-means clustering on embeddings after they have been normalized to be unit length and then whitened. $K = 50$ was used for clustering the 682 segmentation concept embeddings, while $K = 75$ was used for clustering the 1189 classification concept embeddings. Table 2 highlights a few highly-semantic clusters (see Appendix, Section B for all clusters). The differences between the segmentation and classification clusters, as well

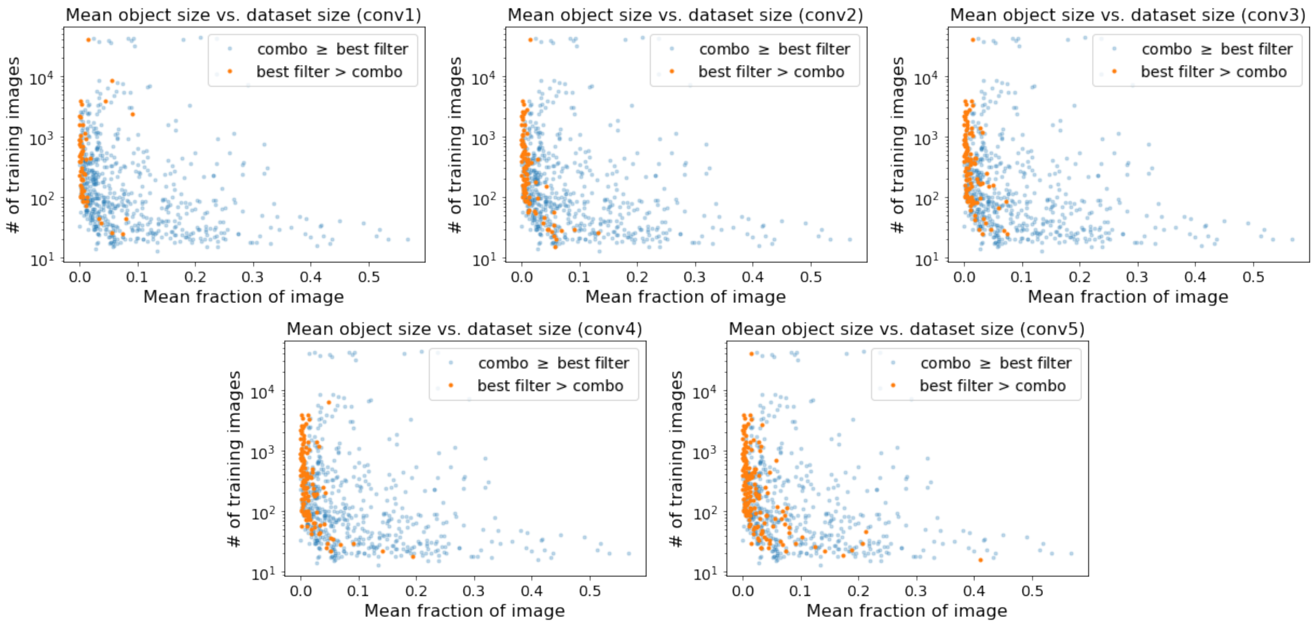


Figure 7. The concepts for which our approach fails to improve upon using the best filter (orange points) for the segmentation task fall into two categories; they either 1., have very few examples (y-axis), or 2., are very small in size (x-axis).

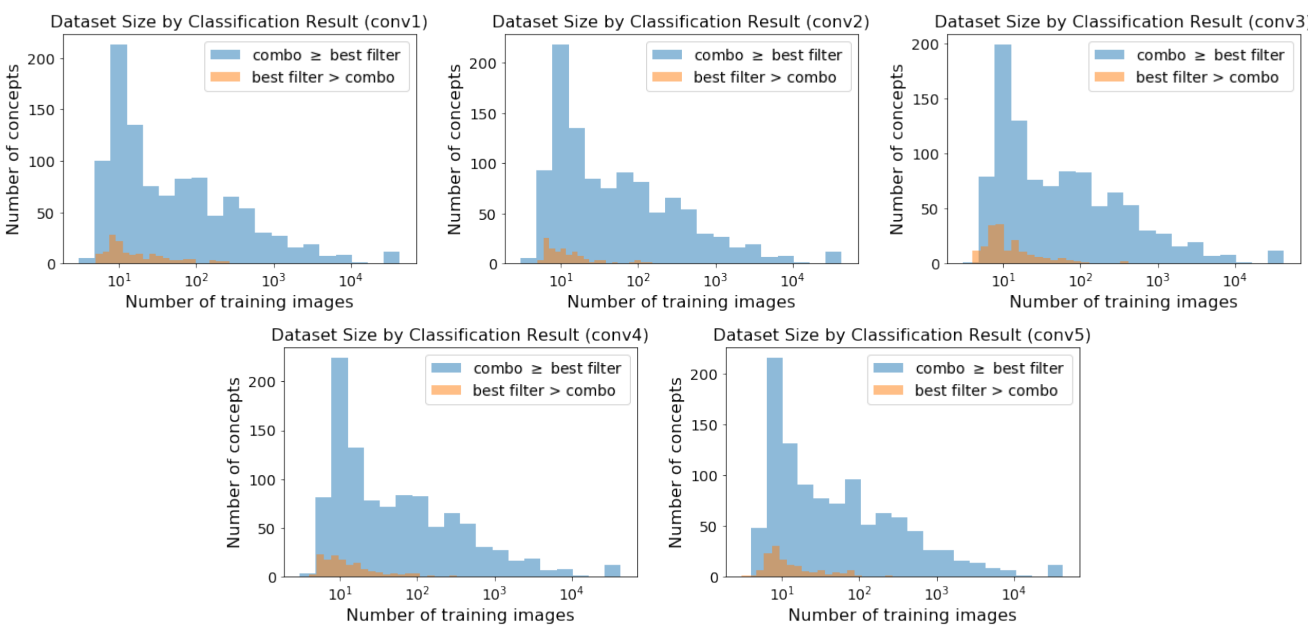


Figure 8. The concepts for which our approach fails to improve upon using the best filter (orange) almost always have very few examples ($< 10^2$).

as the t-SNE visualizations of VOC Pascal classes (Figure 16 and Figure 17), suggests that the different tasks learn different embeddings. In particular, it appears that 'nearby' concepts in the classification embedding space are more sensitive context than those in the segmentation embedding space. For instance, in the t-SNE visualization for conv5 VOC Pascal classification embeddings, outdoor animals are clustered tightly and distinctly away from indoor animals (Figure 16).

3.2.1 Details for Comparing Embeddings from Different Learned Representations

Below, we describe how we computed embeddings for the WordNet and Word2Vec representations. Ultimately we ex-

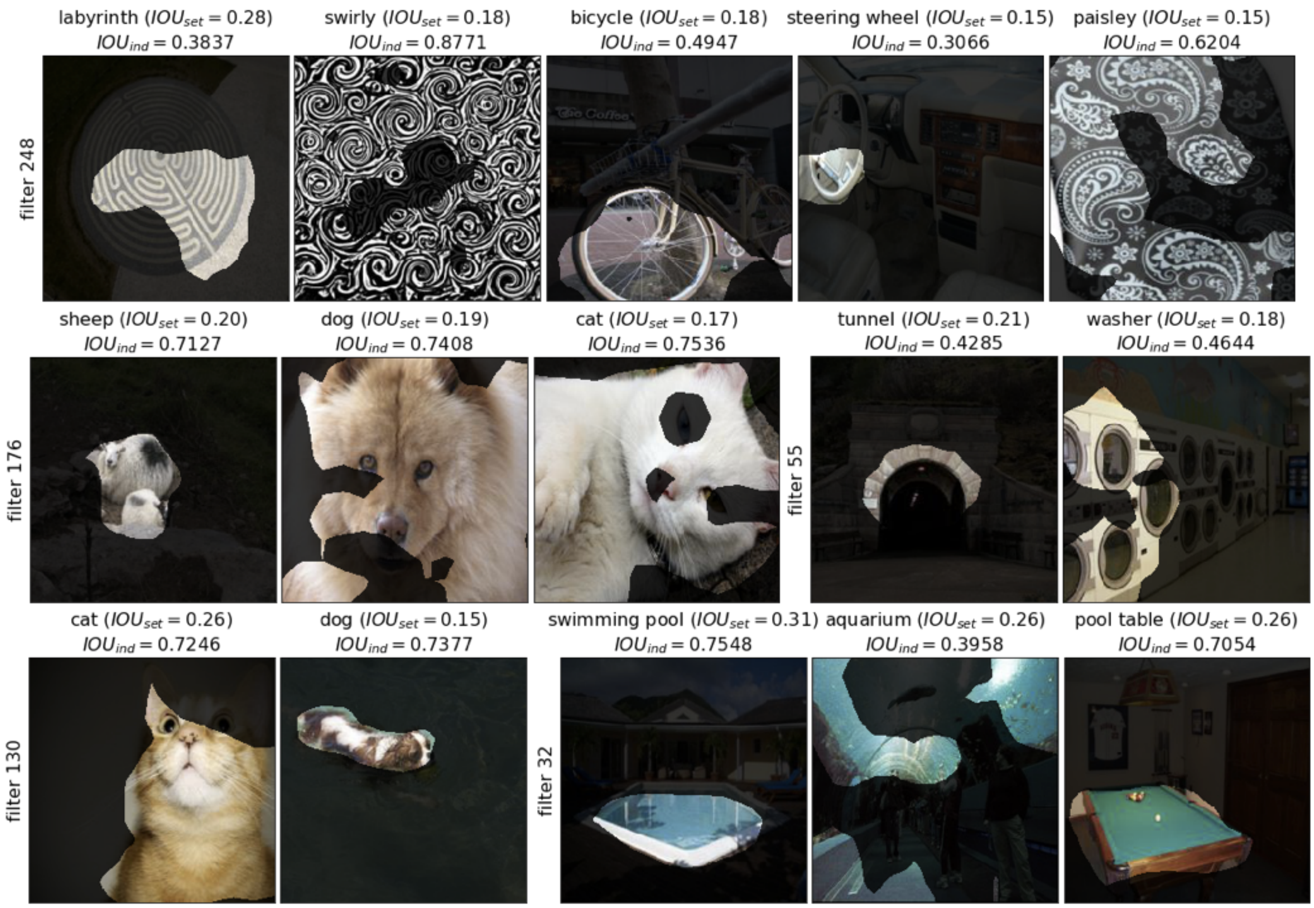


Figure 9. 13 conv5 filters are highly selective ($\mathrm{IoU}_{\mathrm{set}} > 0.15$ on both training and validation sets) for multiple concepts; 5 are shown here and another is shown in depth in main fig. 4. For each concept, the validation example with the highest individual IOU score is shown (masks are upsampled before thresholding for visual smoothness).

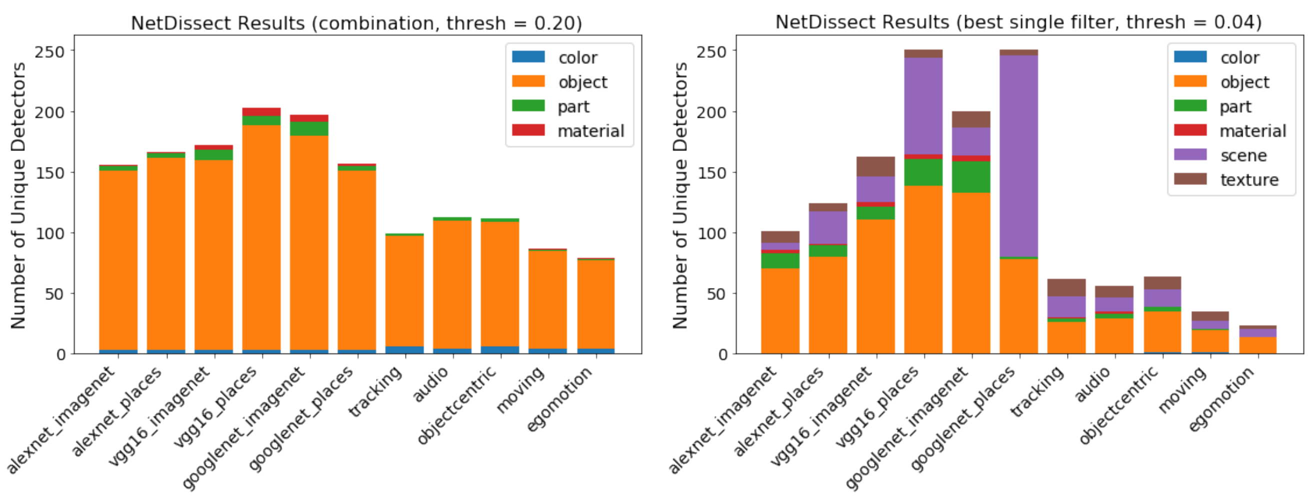


Figure 10. Results for probing different architectures, datasets, and tasks reported using Bau et al.'s style of reporting results by thresholding set IoU scores (i.e., 0.20 threshold for combination and 0.04 threshold for single best filter) and counting the number of unique detectors.

amined the $C = 501$ BRODEN concepts that 1., had segmentation annotations ($N_{seg} = 682$) and 2., have WordNet

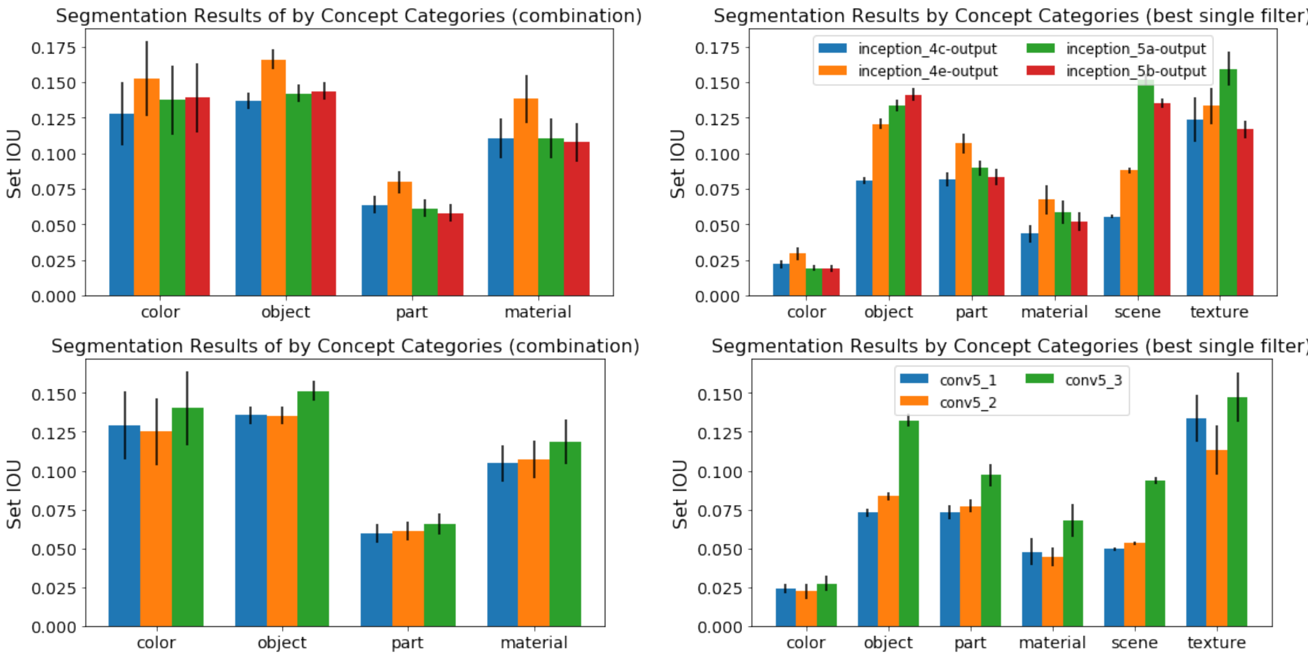


Figure 11. Segmentation results for GoogLeNet (top) and VGG16 (bottom) trained on ImageNet when probing the networks' last few convolutional layers.

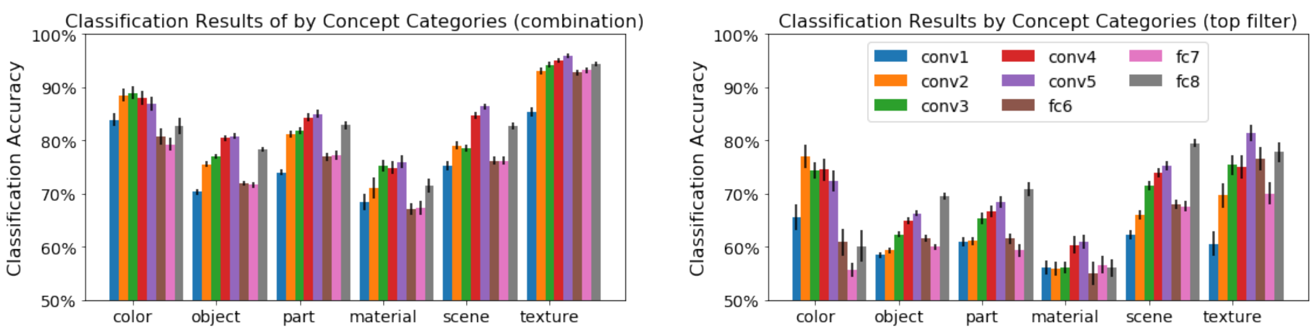


Figure 12. Classification results for AlexNet trained on ImageNet for convolutional and fully connected layers.

and Word2Vec embeddings ($N_{WN} = 937$ and $N_{W2V} = 686$).

WordNet (WN) To learn an embedded representation of BRODEN concepts in WordNet, we first identified all concepts that are both in BRODEN and the WordNet hierarchy ($N_{WN} = 937$). Second, we identified all the unique nodes in the WordNet hierarchy ($M = 1664$) that can be used to compose the hierarchical paths for all 937 BRODEN concepts in WordNet. Third, for each BRODEN concept in WordNet, we constructed a $\mathbb{R}^M$, few-hot vector $\mathbf{w}$: $w_k = 1$ if the k-th WordNet node is part of the hierarchical path description for the given concept; otherwise, $w_k = 0$. Finally, $\mathbf{w}$ was normalized to be unit-length.

Word2Vec (W2V) To learn an embedded representation of BRODEN concepts in Word2Vec, we used an open-source python interface to Word2Vec (`https://github.com/danielfrg/word2vec`) to train a Word2Vec model using 100 dimensions on data from the first 10^8 bytes of Wikipedia English text (`http://mattmahoney.net/dc/text.html`). Then, we identified all the concepts that are both in BRODEN and the Word2Vec vocabulary ($N_{W2V} = 686$).

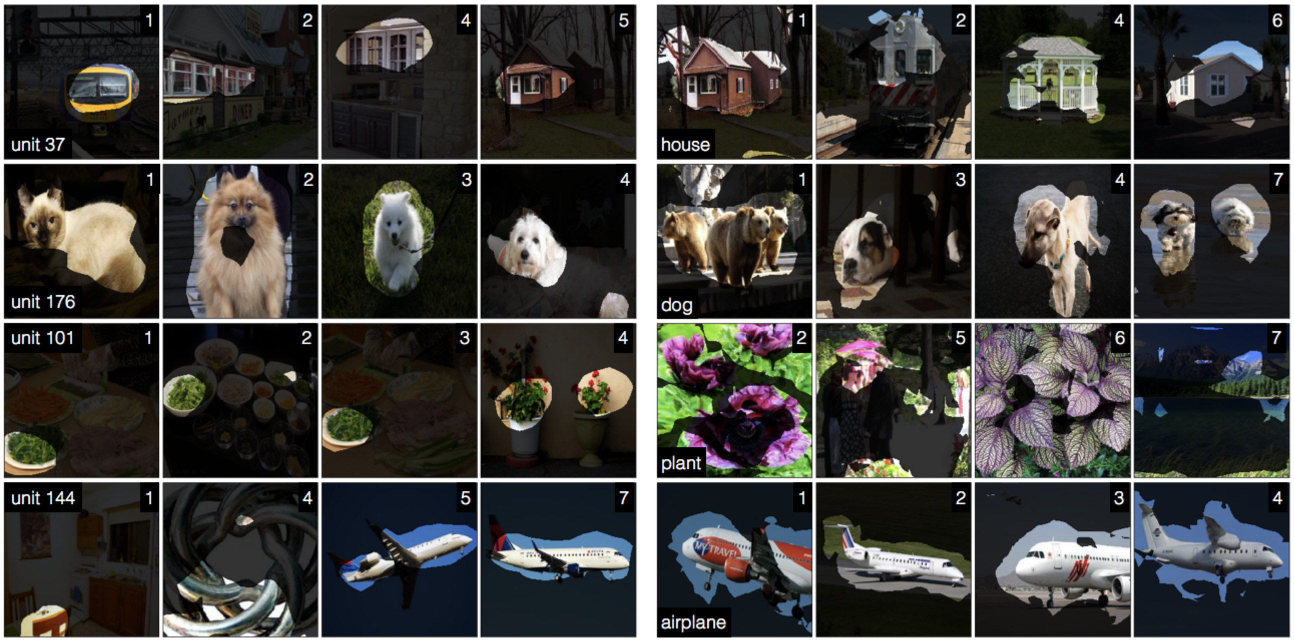


Figure 13. Examples that are maximally activated (rank ordering listed) and aligned to the best conv5 filters (left) and to the learned segmentation weights (right) for 'house', 'dog', 'plant', 'airplane', for comparison with the non-maximal examples in main fig. 8 and fig. 15 (see fig. 14 for maximal activating examples for 'train'). For slightly smoother visualizations, activations were upsampled before being thresholded.

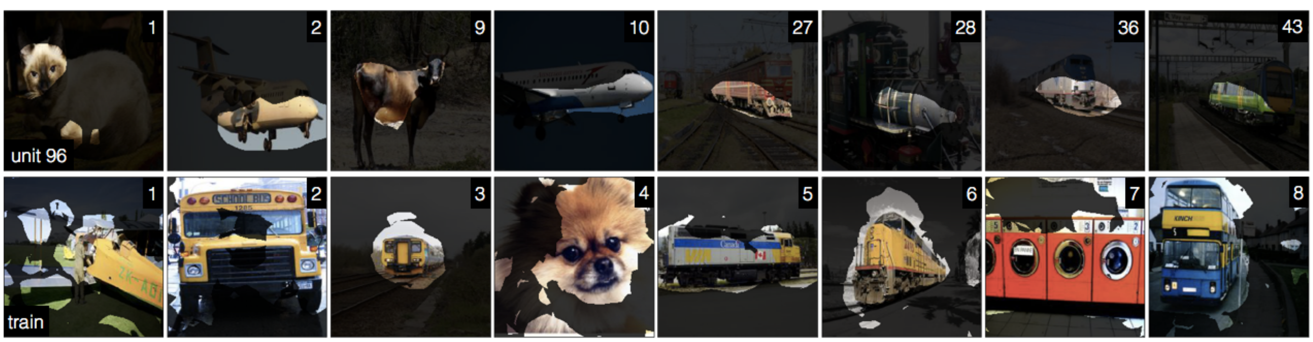


Figure 14. Examples images that are maximally activated (rank ordering listed) and aligned to conv5 filter 96 (top), the best unit for 'train', and to the learned weights (bottom) for segmenting train, for comparison with examples in figs. 13 and 15. Note that in the single filter case, the first train example is the 27th maximally activated example for filter 96. With the exception of the 1st and 4th example, most of the examples that are maximally aligned to the learned weights make sense for 'train' (even the buses and washing machine are 'train'-like in appearance). For slightly smoother visualizations, activations were upsampled before being thresholded.

Table 2. Select K-means clusters of conv5 embeddings ($K = 50$ for segmentation and $K = 75$ for classification; see Appendix, Section B for all clusters).

Segmentation	ear, neck, tail, muzzle, dog, cat, horse, sheep, cow, animal, fur, elephant	person, leg, torso, arm, hand, foot, towel, skin, figurine, apparel	white-c, blue-c, sky, painted, cloud, candelabrum, ice rink	mountain, rock, cliff, ruins, trench, badlands
Classification	head, leg, torso, eye, ear, nose, neck, tail, muzzle, paw, dog, cat	person, arm, hand, hair, mouth, foot, eyebrow	grey-c, white-c, pink-c, purple-c, blue-c	mountain, water, boat, sea, sand, land

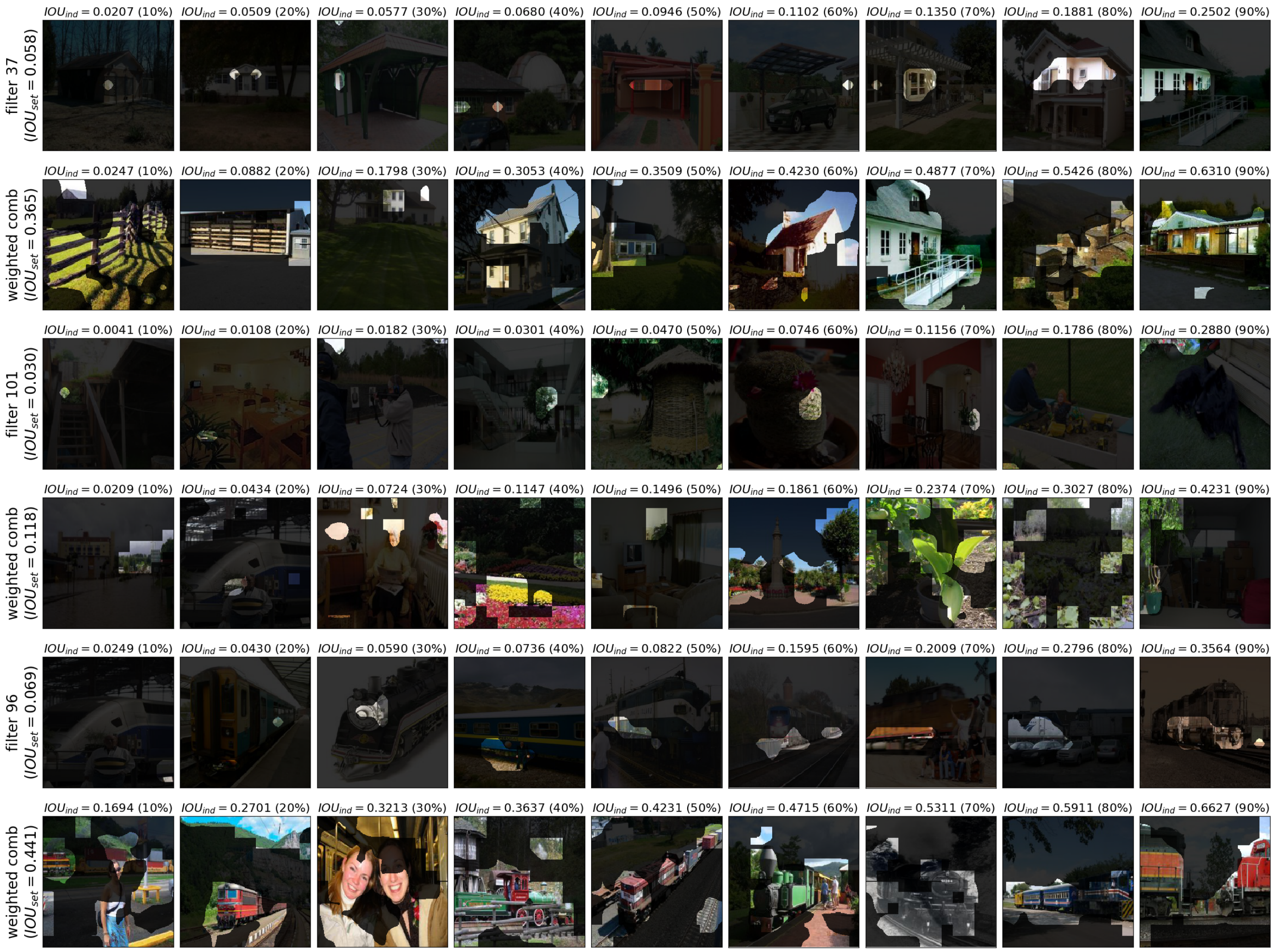


Figure 15. For 'house', 'plant', and 'train' concepts, an example is automatically selected at each decile of the non-zero portion of the distribution of individual IoU score, and the predicted conv5 segmentation masks using the best filter (odd rows) as well as the learned weights (even rows) are overlaid (analogous to main fig. 8 for 'dog' and 'airplane').

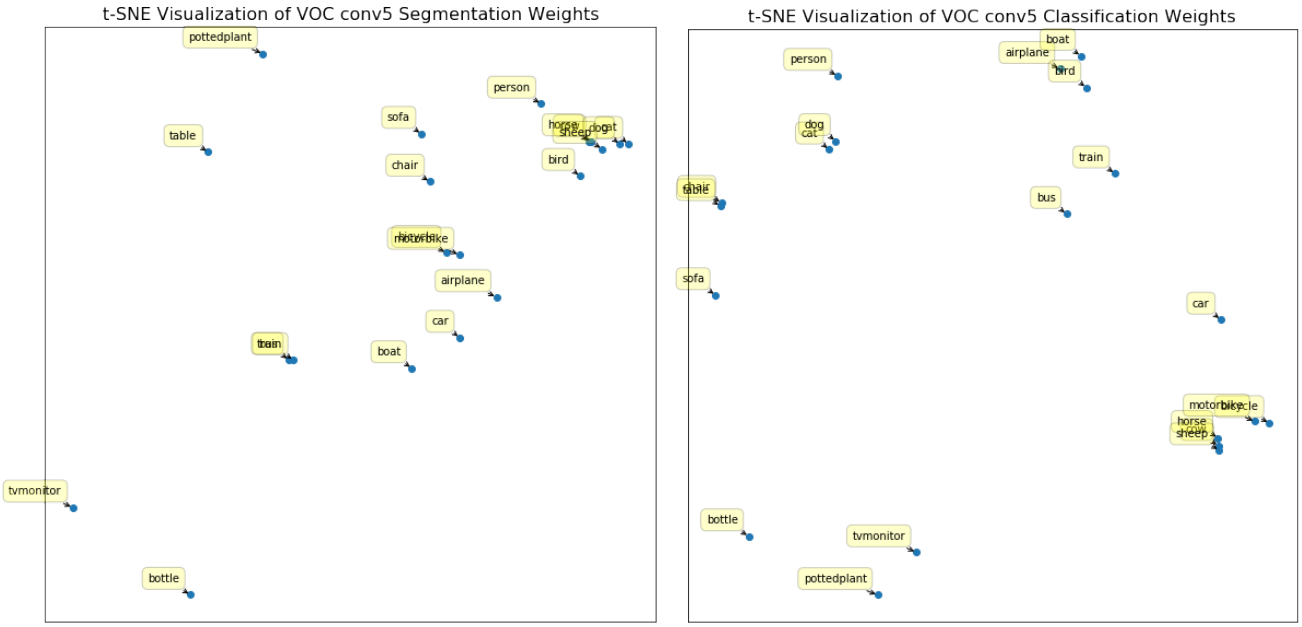


Figure 16. t-SNE visualizations of VOC Pascal concepts' conv5 learned weights (left: segmentation; right: classification). Note that all the vehicles and animals are clustered together in the segmentation embedding space, while the vehicles and animals are further sub-clustered together in the classification embedding space based on the context of the object (i.e., air for 'bird' and 'airplane'; outdoors for 'sheep', 'cow', and 'horse' compared to indoors for 'cat' and 'dog').

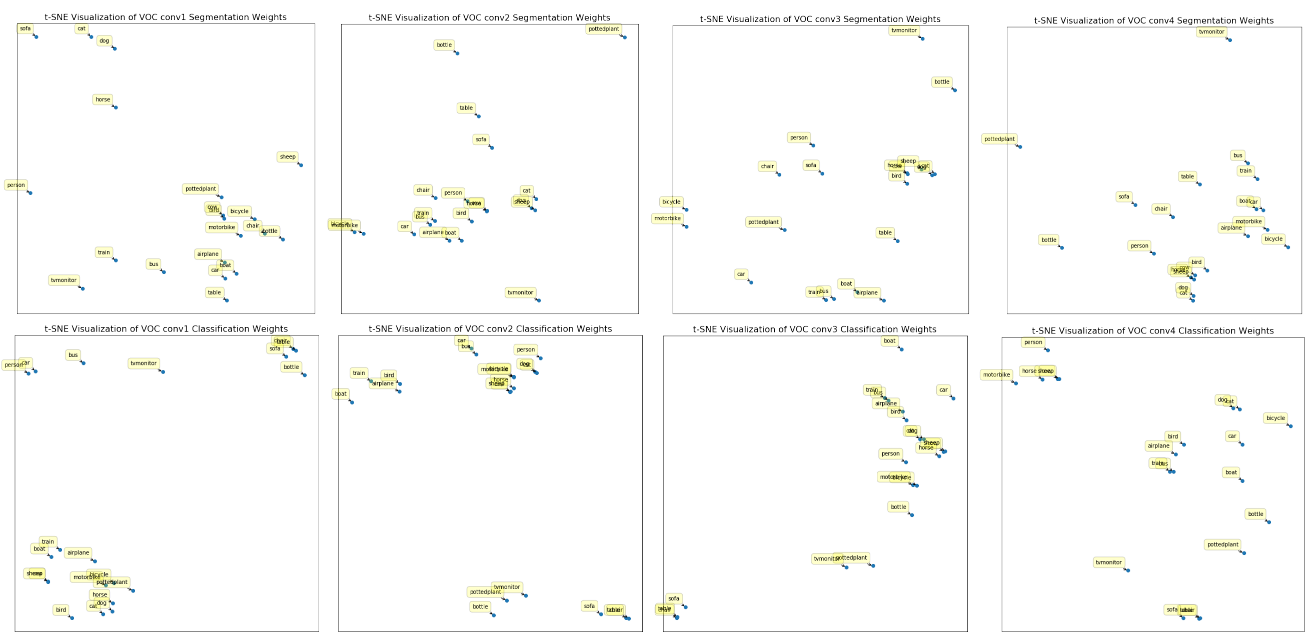


Figure 17. t-SNE visualizations of VOC Pascal concepts' conv1-conv4 learned weights (top row: segmentation; bottom row: classification).

Appendices

A. Filters Encoding Many Concepts

In the main fig. 4, several filters were selected as the best or top filter for many concepts (20+ and 30+ for segmentation and classification respectively). In this section, these units and their associated concepts are listed.

A.1. Segmentation

The conv1-5 units for which over 20 or more concepts selected as the best filter for the segmentation task are listed below (validation IoU_{set} scores for each concept using the given filter are in parentheses).

conv1

1. unit 19: aquarium (0.2461), swimming pool (0.2061), pool table (0.0764), pool (0.0733), screen (0.0532), sea (0.0524), ticket counter (0.0498), fish (0.0347), mouse pad (0.0332), text (0.0323), monitor (0.0300), tvmonitor (0.0299), water (0.0188), lake (0.0141), sand (0.0109), inflatable bounce game (0.0091), plastic-clear (0.0088), tent (0.0073), shower (0.0050), balloon (0.0045), ashcan (0.0026), chain wheel (0.0009), tank (0.0001), wave (0.0000), base (0.0000)
2. unit 21: bird feeder (0.2192), big top (0.1101), ring (0.1076), red-c (0.0976), taillight (0.0529), pack (0.0423), pink-c (0.0384), ottoman (0.0360), cup (0.0336), awning (0.0272), motorbike (0.0208), arm (0.0184), telephone booth (0.0172), umbrella (0.0170), plastic-opaque (0.0162), meat (0.0160), person (0.0159), hat (0.0117), torso (0.0113), towel (0.0111), fabric (0.0092), bedclothes (0.0060), sofa (0.0057), handbag (0.0054), seat (0.0044), slide (0.0043), swivel chair (0.0043), jacket (0.0043), truck (0.0036), leather (0.0036), back pillow (0.0032), banner (0.0032), tapestry (0.0029), seat cushion (0.0026), dishrag (0.0026), armchair (0.0024), table game (0.0021), box office (0.0011), back (0.0009), mat (0.0004), inside arm (0.0001), outside arm (0.0001), henhouse (0.0000), forklift (0.0000)
3. unit 37: leaves (0.1910), field (0.0563), leaf (0.0521), valley (0.0449), green-c (0.0353), grass (0.0333), vineyard (0.0247), pottedplant (0.0232), hedge (0.0177), plant (0.0102), foliage (0.0093), flower (0.0089), pitch (0.0077), fruit (0.0067), brush (0.0062), bench (0.0060), soap dispenser (0.0027), rubber (0.0025), embankment (0.0021), post (0.0012), board (0.0012), ride (0.0012), ship (0.0006), water tank (0.0001), labyrinth (0.0000), cockpit (0.0000), patio (0.0000), metal shutters (0.0000), lockers (0.0000), terraces (0.0000)
4. unit 27: binder (0.1421), doors (0.1198), candelabrum (0.0426), bandstand (0.0315), videos (0.0254), skyscraper (0.0237), book (0.0214), cage (0.0210), folding screen (0.0194), pane of glass (0.0184), exhibitor (0.0179), grill (0.0133), windows (0.0118), building (0.0113), shop window (0.0111), disc case (0.0107), greenhouse (0.0098), windowpane (0.0081), radiator (0.0078), door (0.0068), curtain (0.0068), curtains (0.0066), ladder (0.0061), clock (0.0060), revolving door (0.0058), wall (0.0055), floor (0.0055), cabinet (0.0054), coffee maker (0.0045), gate (0.0045), statue (0.0044), tomb (0.0041), wall socket (0.0038), heater (0.0034), mattress (0.0000), terrace (0.0000)
5. unit 22: quay (0.0907), parking (0.0284), pantry (0.0261), crosswalk (0.0247), bridge (0.0193), altar (0.0140), toll booth (0.0137), riser (0.0135), village (0.0133), equipment (0.0117), controls (0.0098), fountain (0.0091), cabin (0.0091), net (0.0085), display window (0.0084), stove (0.0084), wire (0.0080), shelf (0.0080), pedestal (0.0074), aircraft carrier (0.0067), parterre (0.0064), runway (0.0059), stairway (0.0057), ceiling (0.0055), rope (0.0053), central reservation (0.0052), pipe (0.0047), breads (0.0033)
6. unit 52: orange-c (0.0668), yellow-c (0.0253), blanket (0.0138), food (0.0124), loudspeaker (0.0120), wood (0.0095), tray (0.0085), microphone (0.0078), bread (0.0074), painted (0.0070), booth (0.0051), bird (0.0047), poster (0.0044), tile (0.0034), plate (0.0031), wicker (0.0028), double door (0.0027), cushion (0.0015), vault (0.0010), bar (0.0009), concrete (0.0009), weighbridge (0.0000), linoleum (0.0000), screen door (0.0000), elevator door (0.0000), bread rolls (0.0000)
7. unit 54: scoreboard (0.0341), slats (0.0293), horse-drawn carriage (0.0219), steam shovel (0.0182), boat (0.0168), roof (0.0163), car (0.0160), house (0.0143), hovel (0.0132), grandstand (0.0130), roundabout (0.0128), head roof (0.0086), jar (0.0068), shed (0.0066), dashboard (0.0059), console table (0.0058), tower (0.0054), flowerpot (0.0050), grey-c (0.0038), shipyard (0.0036), air conditioner (0.0031)
8. unit 9: folding door (0.0270), grille door (0.0211), organ (0.0185), scaffolding (0.0167), bookcase (0.0136), altarpiece (0.0134), shops (0.0133), balcony (0.0130), elevator (0.0116), coach (0.0101), railing (0.0086), shutter (0.0083), refrigerator (0.0080), vase (0.0075), sales booth (0.0073), coat (0.0072), bird cage (0.0063), lamp (0.0062), basket (0.0061), chest of drawers (0.0051), cart (0.0042), handle (0.0018), saucepan (0.0015), drum (0.0003)

9. unit 17: silver screen (0.0258), covered bridge (0.0237), wing (0.0199), coach roof (0.0198), desk (0.0182), airplane (0.0169), caravan (0.0161), fireplace (0.0147), sandbox (0.0118), mezzanine (0.0113), pier (0.0107), system (0.0088), computer (0.0088), apron (0.0082), player (0.0074), niche (0.0069), granite (0.0063), metal (0.0062), plane (0.0060), saddle (0.0056), computer case (0.0034), forest (0.0013), conveyer belt (0.0008), fog bank (0.0004)
10. unit 62: document (0.0239), sand trap (0.0234), menu (0.0170), ceramic (0.0165), notebook (0.0133), snow (0.0127), newspaper (0.0125), stretcher (0.0120), napkin (0.0110), laminate (0.0105), monitoring device (0.0104), forecourt (0.0098), lid (0.0090), pillow (0.0089), river (0.0088), fan (0.0085), sink (0.0084), fuselage (0.0083), platform (0.0076), path (0.0070), paw (0.0066), beam (0.0064), dishwasher (0.0051), toilet (0.0048), berth (0.0047), earth (0.0038), price tag (0.0037), iceberg (0.0020), bidet (0.0008), ground (0.0000)

conv2.

1. unit 93: swimming pool (0.1491), aquarium (0.1346), pool table (0.1010), pool (0.0781), playground (0.0382), screen (0.0358), fish (0.0305), sea (0.0263), container (0.0249), monitoring device (0.0183), mouse pad (0.0133), ashcan (0.0110), water (0.0099), net (0.0057), stretcher (0.0015), dental chair (0.0012), base (0.0004), wave (0.0000), boot (0.0000), cockpit (0.0000)
2. unit 31: cage (0.1268), videos (0.0961), pigeonhole (0.0874), bandstand (0.0845), slats (0.0832), bus (0.0524), guardrail (0.0328), balcony (0.0302), book (0.0271), bulletin board (0.0253), grill (0.0223), bookcase (0.0172), building (0.0134), muntin (0.0103), windowpane (0.0097), poster (0.0093), upper sash (0.0092), blind (0.0088), shelf (0.0067), video player (0.0066), folding screen (0.0060), jar (0.0035), tables (0.0000), terrace (0.0000), disc case (0.0000), safety side (0.0000)

conv4. unit 44: bus (0.0974), monitor (0.0888), screen (0.0804), caravan (0.0754), pane of glass (0.0655), shop window (0.0631), television (0.0604), windshield (0.0553), pane (0.0509), railroad train (0.0426), oven (0.0407), autobus (0.0393), computer (0.0390), glass (0.0325), windows (0.0277), blackboard (0.0244), windowpane (0.0174), shutter (0.0109), computer case (0.0074), porch (0.0000), garage door (0.0000)

conv5. unit 1: videos (0.1651), bookcase (0.1427), pantry (0.1162), magazine (0.0764), case (0.0475), bulletin board (0.0465), bottle (0.0386), shelf (0.0379), box (0.0370), booth (0.0365), bag (0.0337), pedestal (0.0321), muntin (0.0283), basket (0.0202), arcade machine (0.0179), stands (0.0138), clock (0.0083), telephone (0.0077), refrigerator (0.0054), bird feeder (0.0000), file cabinet (0.0000), shops (0.0000)

A.1.1 Classification

Below, the 10 conv5 units for which 30 or more concepts selected as the best filter for the classification task are listed below (validation accuracy for each concept using the given filter is in parentheses). The conv1-4 units are excluded due to length, as 13 conv1, 17 conv2, 10 conv3, and 16 conv4 units each were selected for 30 or more concepts. Note: It is possible for the top filter to achieve 100% validation classification accuracy on several concepts for the following reason: Many concepts (particularly scenes) only have a few examples; the way the validation set is constructed is by creating a random, balanced one-vs-rest set. For concepts with few examples, it is more possible to learn a single filter weight with which to achieve 100% classification accuracy.

conv5.

1. golf_course-s (1.00), waterfall-cascade-s (1.00), kiosk-outdoor-s (1.00), water_tower-s (1.00), bow_window-outdoor-s (0.94), fairway-s (0.93), roundabout (0.89), utility_room-s (0.88), forklift (0.83), ship (0.83), table game (0.83), barrels (0.82), river-s (0.82), studded (0.78), scaffolding (0.76), dome (0.76), bus_depot-outdoor-s (0.75), ranch-s (0.75), escalator-outdoor-s (0.75), assembly_line-s (0.70), vent (0.70), flag (0.67), sandbox-s (0.67), pitted (0.63), footbridge (0.63), tap (0.63), shoe_shop-s (0.59), fountain (0.59), backpack (0.59), curtains (0.58), disc case (0.50), booth-indoor-s (0.50), apse-indoor-s (0.50), fireplace (0.49), stands (0.29), pictures (0.17), shipyard (0.17)
2. ocean-s (1.00), volleyball_court-outdoor-s (1.00), mountain_path-s (1.00), videostore-s (0.94), cavern-indoor-s (0.88), casino-outdoor-s (0.83), control tower (0.83), slum-s (0.83), dam (0.83), subway_station-platform-s (0.83), niche (0.83), waterfall-fan-s (0.80), house-s (0.77), soap dispenser (0.76), watchtower (0.75), watchtower-s (0.75), barn-s (0.75), courtroom-s (0.75), bidet (0.71), parlor-s (0.68), irrigation_ditch-s (0.67), junk_pile-s (0.67), billboard (0.64), village (0.62), cage (0.61), landing-s (0.60), dining_car-s (0.58), aqueduct (0.57), berth-s (0.56), crate (0.50), kasbah-s (0.50), viaduct-s (0.50)

3. windscreen (1.00), monument (0.94), banquet_hall-s (0.88), locker_room-s (0.88), shop (0.83), church-indoor-s (0.82), menu (0.80), crosswalk (0.78), safety side (0.75), faucet (0.75), windshield (0.74), toilet (0.74), boot (0.73), duck (0.73), marbled (0.73), coffee maker (0.71), binder (0.70), art_gallery-s (0.69), fastfood_restaurant-s (0.67), bicycle (0.65), hen (0.64), pitcher (0.64), escalator (0.62), window_seat-s (0.58), chimney (0.51), steering wheel (0.50), top (0.50), bar (0.48), airport_terminal-s (0.27)
4. cathedral-outdoor-s (1.00), lake-artificial-s (1.00), moon_bounce-s (1.00), pavilion (1.00), shelter (0.94), altarpiece (0.92), shower-s (0.89), zen_garden-s (0.88), carrousel-s (0.83), courthouse-s (0.79), archive-s (0.78), ballroom-s (0.78), earmuffs (0.75), barbershop-s (0.75), covered_bridge-interior-s (0.75), porous (0.73), flight_of_stairs-urban-s (0.67), earth_fissure-s (0.67), attic-s (0.61), inn-outdoor-s (0.50), bakery-kitchen-s (0.50), can (0.42), mine-s (0.42)
5. grille door (1.00), tennis court (1.00), vineyard (1.00), formal_garden-s (1.00), semidesert ground (1.00), swimming_pool-indoor-s (1.00), cabana-s (1.00), palace-s (1.00), vegetable_garden-s (1.00), snowfield-s (1.00), fitting_room-exterior-s (1.00), bullpen-s (1.00), nunnery-s (1.00), lined (0.94), videos (0.94), ruins (0.92), hot_spring-s (0.92), freckled (0.91), heliport-s (0.90), spiralled (0.89), ball_pit-s (0.88), campsite-s (0.88), stratified (0.87), polka-dotted (0.87), harbor-s (0.86), mosque-outdoor-s (0.86), lacelike (0.85), butchers_shop-s (0.83), manufactured_home-s (0.83), checkout_counter-s (0.83), tearoom-s (0.83), tower-s (0.82), price tag (0.81), dacha-s (0.80), fire_escape-s (0.80), liquor_store-outdoor-s (0.80), television_studio-s (0.80), corridor-s (0.80), carport (0.78), arch-s (0.78), bullring (0.75), pantry-s (0.75), canvas (0.75), lean-to-s (0.75), fjord-s (0.75), elevator-interior-s (0.75), gauzy (0.74), briefcase (0.73), art_studio-s (0.73), television stand (0.72), classroom-s (0.72), wet_bar-s (0.71), hot tub (0.70), cash register (0.70), parterre (0.68), folding door (0.67), fish (0.67), construction_site-s (0.67), recycling bin (0.67), bridge (0.66), windows (0.66), dinette-home-s (0.65), movie_theater-outdoor-s (0.62), fort-s (0.62), brewery-outdoor-s (0.62), food_court-s (0.62), player (0.61), stile (0.61), catwalk-s (0.60), mosque-indoor-s (0.60), napkin (0.59), rubble (0.58), ladder (0.57), sewing machine (0.57), plane (0.55), lobby-s (0.54), stretcher (0.50), chicken_coop-outdoor-s (0.50), tracks (0.50), reading_room-s (0.50), pulpit-s (0.50), gymnasium-indoor-s (0.50), face (0.47), water wheel (0.25)
6. ski_resort-s (1.00), shopfront-s (1.00), ruin-s (1.00), carport-outdoor-s (1.00), diner-outdoor-s (1.00), planetarium-outdoor-s (1.00), tomb (1.00), supermarket-s (1.00), aquatic_theater-s (1.00), beach-s (0.98), parking_lot-s (0.95), striped (0.94), airport-s (0.92), kindergarden_classroom-s (0.92), home_theater-s (0.92), hacienda-s (0.90), observatory-outdoor-s (0.90), warehouse-indoor-s (0.89), lighthouse-s (0.88), covered_bridge-exterior-s (0.88), topiary_garden-s (0.88), sky (0.87), escalator-indoor-s (0.83), park-s (0.83), doors (0.83), land (0.82), lid (0.82), desert-sand-s (0.82), field (0.81), workbench (0.81), cross (0.81), controls (0.80), mouth (0.79), wire (0.79), revolving door (0.79), waterfall-block-s (0.79), dining_room-s (0.78), closet-s (0.76), baseboard (0.75), pool (0.75), sandbar-s (0.75), cemetery-s (0.75), baggage_claim-s (0.75), fog bank (0.75), viaduct (0.75), shirt (0.75), shanties (0.75), towel (0.74), jacuzzi-indoor-s (0.74), earth (0.73), bookcase (0.73), cliff (0.72), inn-indoor-s (0.71), waterfall (0.71), footboard (0.71), butte-s (0.70), apron (0.69), leaves (0.69), fabric (0.68), neck (0.67), crane (0.66), wallpaper (0.65), washer (0.65), office-s (0.65), track (0.64), arch (0.64), aircraft carrier (0.64), convenience_store-outdoor-s (0.62), ramp (0.62), elevator_lobby-s (0.62), dam-s (0.62), mirror (0.62), minibike (0.60), bedroom-s (0.60), paper (0.60), living_room-s (0.59), radio (0.59), rock (0.59), painting (0.58), fur (0.58), cushion (0.57), eyebrow (0.57), gravestone (0.56), bottle (0.56), guardrail (0.55), embankment (0.55), wall (0.55), oven (0.53), grill (0.53), magazine (0.53), back (0.51), shower curtain (0.50), lecture_room-s (0.50), elephant (0.50), freeway-s (0.50), beauty_salon-s (0.46), video player (0.43), console table (0.41), side rail (0.41), television camera (0.40), fence-s (0.38), hospital-s (0.25), trestle (0.25), badminton_court-indoor-s (0.00)
7. mountain pass (1.00), auditorium-s (0.88), button panel (0.81), bouquet (0.79), hedge (0.78), pane of glass (0.77), wing (0.77), food (0.76), rim (0.74), bumper (0.73), building_facade-s (0.73), nursery-s (0.71), taillight (0.70), sea (0.68), student_residence-s (0.67), curb (0.66), central reservation (0.65), step (0.62), screen (0.62), blinds (0.61), granite (0.58), pillar (0.55), pedestal (0.53), cap (0.50), wardrobe (0.49), linoleum (0.46), heater (0.45)
8. pagoda-s (1.00), bank_vault-s (1.00), air_base-s (1.00), slope (1.00), farm-s (1.00), parking lot (1.00), dental chair (0.90), catwalk (0.90), field-wild-s (0.89), barnyard-s (0.88), bread (0.86), fuselage (0.84), imaret-s (0.83), arcades (0.83), merchandise (0.83), access_road-s (0.83), elevator-freight_elevator-s (0.75), joss_house-s (0.75), rudder

(0.75), clothing_store-s (0.75), awning (0.75), conference_room-s (0.72), trouser (0.71), dirt track (0.70), bar-s (0.69), bedpost (0.69), horse-drawn carriage (0.69), ticket window (0.67), cactus (0.67), telescope (0.67), subway_station-corridor-s (0.62), coat (0.58), planter (0.56), crt screen (0.55), basketball hoop (0.50), display board (0.50), weighbridge-s (0.50), roller coaster (0.50), baptismal font (0.50), playground-s (0.36)
9. gift_shop-s (1.00), fishpond-s (1.00), bread rolls (1.00), industrial_area-s (1.00), mission-s (1.00), tumble dryer (1.00), paisley (0.98), cracked (0.94), library-indoor-s (0.93), perforated (0.88), hoof (0.86), goal (0.86), bakery-shop-s (0.86), buffet (0.84), guardhouse-s (0.83), equipment (0.82), pier (0.81), desert (0.80), carport-freestanding-s (0.80), planks (0.80), hangar-outdoor-s (0.79), parking_garage-outdoor-s (0.75), computer_room-s (0.75), witness stand (0.75), building_complex-s (0.75), bridge-s (0.74), upper sash (0.73), museum-indoor-s (0.73), casino-indoor-s (0.73), sash (0.72), bus stop (0.70), cd (0.70), restaurant-s (0.70), castle-s (0.68), calendar (0.68), deck chair (0.67), tower (0.67), tables (0.67), excavation-s (0.67), bow_window-indoor-s (0.67), grand piano (0.64), synthesizer (0.64), box office (0.64), jacket (0.64), fire place (0.63), hotel_breakfast_area-s (0.62), easel (0.60), acropolis (0.60), wineglass (0.57), mat (0.56), fruit (0.55), hospital_room-s (0.50), courtyard-s (0.50), display window (0.50), carousel (0.50), bazaar-outdoor-s (0.50), signal_box-s (0.50), meat (0.50), patio (0.43)
10. island (0.94), balcony-interior-s (0.88), helmet (0.88), manhole (0.82), airplane (0.81), palm (0.79), monitor (0.76), autobus (0.71), machine (0.68), stained (0.65), brick (0.63), basket (0.59), foot (0.57), kitchen-s (0.52), ottoman (0.52), statue (0.51), loudspeaker (0.51), doorframe (0.51), bell (0.47)

B. Concept Embedding Clusters

B.1. Segmentation Concept Embeddings

Below is the full list of $K = 50$ clusters for the 682 classification concepts using their conv5 learned weights (concepts with '-c' denote colors):

1. camera
2. faucet, work surface, skylight, table tennis, table game
3. box, bottle, shelf, book, pedestal, bookcase, magazine, merchandise, pallet, stands, pantry, videos
4. shelter, hay
5. clock, bench, drinking glass, trade name, keyboard, blind, button panel, case, mug, grandstand, pier, trunk, microphone, place mat, baby buggy, decoration, piano, table football, video player, railway, coach roof, ring, synthesizer, barrels, binder, tables, terraces, shore
6. plane, television camera, steam shovel
7. shade, toilet, lid, water tank, bidet, dental chair
8. building, railing, house, balcony, fluorescent, canopy, stile, buffet, windows, scaffolding, carousel, terrace, dam, disc case, shanties, temple
9. ice, plastic
10. ceiling, metal, light, vase, mouse, curb, pool table, vent, system, tank, swimming pool, sill, bell, briefcase, mouse pad, earmuffs, tire, display board, ramp, pool, shop, aquarium, tomb, canvas
11. grass, sidewalk, earth, path, field, sand, snow, manhole, central reservation, land, stage, embankment, dirt track, altar, forecourt, calendar, deck, valley, patio, straw, windscreen, desert, semidesert ground, vineyard, rubble, sandbox, catwalk, parking lot, bullring, shipyard
12. mountain, rock, cliff, ruins, trench, badlands
13. flowerpot, pottedplant, palm, foliage, leaves, leaf
14. grey-c, road, water, sea, river, concrete, lake, pond, mountain pass
15. tower, ship, lighthouse, vault, windmill, water tower, watchtower
16. car, lamp, headlight, body, license plate, stove, spotlight, boat, rim, taillight, windshield, van, cap, airplane, beak, stern, saddle, engine, bumper, pack, handbag, wineglass, backpack, face, kettle, washer, helmet, drawing, saucepan, fuselage, grand piano, cockpit, gas pump, steering wheel, box office, forklift, recycling bin, machinery, dashboard, parking, barbecue, meter, rudder
17. person, leg, torso, arm, hand, foot, towel, skin, figurine, apparel
18. paw, wing, bird, horn, duck, hen
19. wheel, bicycle, traffic light, stool, motorbike, beam, blade, crane, fire escape, horse-drawn carriage, wheelchair, roller coaster, water wheel, excavator, hand cart
20. mirror, column, frame, exhaust hood, shutter, soap dispenser, computer case, metal shutter, casing, shaft, capital, basketball hoop, television stand, porch, scoreboard, revolving door, doors, shops, shower curtain, gas station, niche, toll booth
21. wall, door, curtain, pillar, door frame, wardrobe, side, doorframe, jacket, curtains, coat, lockers
22. white-c, blue-c, sky, painted, cloud, candelabrum, ice rink
23. roof, awning, umbrella, dome, tent, conveyer belt, carport, shed, big top, covered bridge
24. ear, neck, tail, muzzle, dog, cat, horse, sheep, cow,

animal, fur, elephant

25. pole, fence, skyscraper, hoof, grill, bulletin board, rack, cradle, tapestry, garage door, file cabinet, equipment, cage, elevator, controls, folding screen, bird cage, folding door, bird feeder, slats, grille door, safety side
26. chair, sofa, back, seat, armchair, pillow, seat cushion, leather, back pillow, seat base, inside arm, outside arm, swivel chair, ottoman, wicker, traveling bag, jersey, planks
27. flower, food, bag, basket, chandelier, tray, plastic-clear, jar, fruit, ball, bouquet, patty, fire, breads, bread rolls, candies
28. podium, ticket counter
29. green-c, yellow-c, tree, plant, streetlight, bush, hill, hedge, brush, shower stall, island, slope, brushes, roundabout, forest, vegetables
30. brick, wallpaper
31. fabric, bed, cushion, bathtub, bedclothes, blanket, stretcher, eiderdown, mat, berth
32. fan, handle bar, sculpture, chain wheel, minibike, shoe, backplate, rubbish, cannon, skeleton
33. bannister, bridge, entrance, footbridge, arcade, arch, arcades, gravestone, tunnel, aqueduct, bandstand, service station, trellis, washing machines, mosque, viaduct, trestle, acropolis
34. signboard, paper, plaything, truck, poster, flag, telephone, bucket, train, bus, coach, cardboard, autobus, container, text, coffee maker, hat, banner, booth, vending machine, telephone booth, cart, arcade machine, head roof, railroad train, exhibitor, fish, gym shoe, slot machine, playground, balloon, ad, helicopter, trailer, display window, slide, pictures, caravan, ride, bulldozer, inflatable bounce game, book stand
35. platform, escalator, bowling alley, skittle alley
36. plastic-opaque, ceramic, pot, sink, plate, bowl, cup, laminate, hot tub, barrel
37. windowpane, pane, double door, shop window, pane of glass, screen door, sash, lower sash, upper sash, ticket window
38. court, pitch, goal, tennis court, witness stand
39. chimney, runway, hovel, bus stop, bedpost, sand trap, cabin, greenhouse, structure, henhouse, village, cactus, labyrinth, baptismal font
40. brown-c, orange-c, wood, counter
41. head, eye, nose, hair, mouth, eyebrow, oar
42. black-c, ground, handle, wall socket, knob, sconce, headboard, rope, shelves, candlestick, microwave, pipe, air conditioner, can, knife, gate, radiator, candle, pitcher, remote control, bar, ladder, arm panel, fork, notebook, toilet tissue, muntin, heater, booklet, post, shower, spoon, printer, teapot, document, tap, statue, postbox, dormer, wire, console table, dishrag, paper towel, partition, corner pocket, spindle, towel rack, diffusor, side rail, deck chair, canister, net, shirt, easel, newspaper, cross, streetcar, trouser, billboard, plinth, cash register, rocking chair, bread, baseboard, clouds, scale, radio, boot, stabilizer, dummy, mezzanine, map, menu, guardrail, mattress, sweater, aircraft carrier, price tag, metal shutters, bottle rack, pulpit, finger, monument, workbench, altarpiece, planter, player, blinds, control tower, weighbridge, mill, organ, parterre, pavilion, parasol, sewing machine, rifle, telescope, drum, stalls, check-in-desk, set of instruments, fog bank, table cloth, bathrobe, crate, quay
43. stairs, stairway, step, crosswalk, riser, tread, pigeonhole
44. fountain, waterfall, smoke, wave, iceberg
45. cabinet, drawer, chest of drawers, footboard, front, kitchen island
46. base, ashcan, switch, rubber, machine, panel
47. table, top, coffee table, desk, apron, countertop, napkin, chest, guitar, cd
48. pink-c, purple-c, red-c, meat
49. glass, painting, screen, television, tvmonitor, fireplace, oven, refrigerator, computer, board, loudspeaker, dishwasher, monitor, crt screen, monitoring device, laptop, silver screen, sales booth, fridge, blackboard, fire place, tumble dryer, elevator door, instrument panel
50. floor, carpet, tile, granite, track, skirt, linoleum, tracks, gravel

B.2. Classification Concept Embeddings

Below is the full list of $K = 75$ clusters for the 1189 classification concepts using their conv5 learned weights (concepts with '-s' and '-c' denote scenes and colors respectively):

1. truck, traffic light, poster, trade name, shop window, minibike, manhole, crosswalk, umbrella, autobus, container, shutter, text, curb, central reservation, post, metal shutter, cloud, windows, crane, postbox, trunk, banner, booth, alley-s, telephone booth, sales booth, scaffolding, billboard, garage-indoor-s, roundabout-s, bus stop, ad, metal shutters, roundabout, terrace, revolving door, parterre, forklift, crosswalk-s, bus_shelter-s
2. woven, meshed, grid, zigzagged, window_seat-s, bow_window-indoor-s, archive-s, bow_window-outdoor-s, atrium-public-s, doorway-outdoor-s, shopfront-s, balcony-exterior-s, jail-indoor-s, wine_cellar-bottle_storage-s, anechoic_chamber-s, bedchamber-s, throne_room-s
3. side, front, radiator, face, rack, waiting_room-s, cradle, childs_room-s, nursery-s, slats, safety side

4. pillar, pedestal, counter, fluorescent, bulletin board, handbag, pane of glass, traveling bag, airport_terminal-s, partition, diffusor, vending machine, art_gallery-s, reception-s, exhibitor, briefcase, elevator, table football, coat, shop, ticket counter, check-in-desk, food_court-s, airport_ticket_counter-s, cafeteria-s
5. plant, carpet, lamp, shelf, railing, cushion, book, flower, back, shade, seat, vase, flowerpot, armchair, base, double door, door frame, stool, fan, step, figurine, magazine
6. building_facade-s, dormer, apartment_building-outdoor-s, forecourt, monument, office_building-s, courthouse-s, mansion-s, bandstand, doors, inn-outdoor-s, diner-outdoor-s, courtyard-s, hospital-s, bank-outdoor-s, embassy-s, casino-outdoor-s, hotel-outdoor-s, student_residence-s, general_store-outdoor-s, synagogue-outdoor-s, quadrangle-s, signal_box-s, fire_station-s, pub-outdoor-s
7. head, leg, torso, eye, ear, nose, neck, tail, muzzle, paw, dog, cat
8. can, fridge, calendar, mouse pad, cd, linoleum, video player, player, disc case
9. grandstand, net, court, basketball hoop, pitch, scoreboard, ice rink, ring, goal, ice_skating_rink-indoor-s, tennis court, boxing_ring-s, stadium-baseball-s, badminton_court-outdoor-s, basketball_court-outdoor-s, badminton_court-indoor-s, basketball_court-indoor-s, football_field-s, bullpen-s, bleachers-indoor-s
10. airplane, stern, engine, highway-s, plane, runway, smoke, fuselage, stabilizer, parking_lot-s, arrival_gate-outdoor-s, guardrail, aircraft carrier, cockpit, access_road-s, landing_deck-s, slope, helicopter, finger, trailer, parking_garage-indoor-s, control tower, lecture_room-s, parking, runway-s, airport-s, hangar-indoor-s, flood-s, gas station, heliport-s, air_base-s, car_dealership-s, skeleton
11. field, pasture-s, field-cultivated-s, field-wild-s, valley-s, hill-s, golf_course-s, fairway-s, cemetery-s, sand trap, hayfield-s, hay, marsh-s, corn_field-s, corral-s, farm-s, wheat_field-s, moor-s, ranch_house-s, ranch-s, fence-s, vineyard-s, vineyard, lawn-s, baseball_field-s, savanna-s, oasis-s, volleyball_court-outdoor-s, driving_range-outdoor-s, bog-s, cactus, batters_box-s, watering_hole-s, barnyard-s, field_road-s, bayou-s
12. arcade machine, fish, amusement_arcade-s, ball_pit-s, ride, moon_bounce-s, inflatable bounce game
13. foliage, rubbish, clothing_store-s, market-outdoor-s, carousel, florist_shop-indoor-s, sandbox-s, carrousel-s, rifle, bird feeder, barbecue, junk_pile-s, bazaar-indoor-s, butchers_shop-s, catwalk-s, market-indoor-s, catwalk, bazaar-outdoor-s, banquet_hall-s, beer_garden-s, junkyard-s, florist_shop-outdoor-s, meat
14. patty, bakery-shop-s, warehouse-indoor-s, cash register, bread, shoe_shop-s, dummy, merchandise, pantry-s, bookstore-s, pallet, supermarket-s, price tag, library-indoor-s, display window, delicatessen-s, shopping_mall-indoor-s, videostore-s, reading_room-s, stands, pantry, videos, shops, breads, candy_store-s, ice_cream_parlor-s, bread rolls, tables, candies, liquor_store-indoor-s, bakery-kitchen-s, gift_shop-s, convenience_store-indoor-s, book stand
15. lighthouse, lighthouse-s, windmill, water tower, control_tower-outdoor-s, water_tower-s, geodesic_dome-outdoor-s, windmill-s, planetarium-outdoor-s, watchtower, observatory-outdoor-s, watchtower-s, nuclear_power_plant-outdoor-s, building_complex-s
16. fibrous, veined, marbled, matted, cracked, potholed, stratified, wrinkled, lacelike, cobwebbed, cavern-indoor-s, mine-s, dirt_track-s, hoodoo-s, gulch-s, hot_tub-indoor-s, covered_bridge-interior-s, archaelogical_excavation-s, catacomb-s
17. grey-c, white-c, pink-c, purple-c, blue-c
18. mountain_snowy-s, mountain-s, coast-s, beach-s, river-s, cliff, clouds, lake-natural-s, ice, valley, duck, waterfall-block-s, badlands-s, ocean-s, desert-sand-s, trench, snowfield-s, islet-s, ski_resort-s, wave, canyon-s, desert, hot_spring-s, sandbar-s, desert-vegetation-s, semidesert ground, ski_slope-s, crevasse-s, estuary-s, mountain_road-s, badlands, forest, lagoon-s, road_cut-s, iceberg, fog bank, hot_tub-outdoor-s, fjord-s, butte-s, earth_fissure-s, mountain pass
19. ladder, youth_hostel-s, mattress, bedpost, cubicle-library-s
20. train, bus, track, coach, platform, head roof, railroad train, railway, coach roof, ramp, tracks, auto_factory-s, bleachers-outdoor-s, train_station-outdoor-s, carport-freestanding-s
21. paper, screen, desk, tvmonitor, keyboard, computer, swivel chair, loudspeaker, mouse, monitor, crt screen, monitoring device, laptop, mug, remote control, notebook, booklet, computer case, printer, document, office-s, home_office-s, system, television stand, display board, cubicle-office-s, computer_room-s, music_studio-s
22. bottle, pot, body, pottedplant, cup, cap, wineglass
23. pool table, ball, conference_room-s, game_room-s, poolroom-home-s, corner pocket, swimming pool, table tennis, poolroom-establishment-s, swimming_pool-outdoor-s, swimming_pool-indoor-s
24. staircase-s, baseboard, riser, panel, tread, fire place, wet_bar-s, artists_loft-s, basement-s, hallway-s, ballroom-s, curtains, bottle rack, doorway-

indoor-s, alcove-s, elevator door, folding door, sauna-s, courtroom-s, barrels, kitchenette-s, elevator_lobby-s, shower curtain, niche, elevator-door-s, spa-massage_room-s, bathrobe, landing-s, funeral_chapel-s

25. flag, palm, chimney, sculpture, skyscraper-s, bridge, skyscraper, concrete, hedge, tower, dome, fountain, arch, tower-s, cannon, pagoda-s, downtown-s, brewery-outdoor-s, freeway-s
26. motorbike, backpack, brush, helmet, baby buggy, wheelchair
27. entrance, castle-s, arcade, arcades, plaza-s, abbey-s, gravestone, planter, ruins, aqueduct, church-outdoor-s, mosque-outdoor-s, aqueduct-s, tomb, monastery-outdoor-s, kasbah-s, viaduct-s, baptistry-outdoor-s, arch-s, donjon-s, ruin-s, town_house-s, palace-s, cathedral-outdoor-s, ghost_town-s, moat-water-s, cloister-outdoor-s, hacienda-s, mosque, viaduct, mausoleum-s, imaret-s, mission-s, nunnery-s, jail-outdoor-s, acropolis
28. mirror, drawer, knob, sconce, basket, pane, switch, chest of drawers, frame
29. wing, bird, beak
30. metal, tile, plastic-opaque, granite, ceramic, food, plastic-clear, laminate, skin, cardboard
31. bed, bedroom-s, pillow, headboard, clock, plaything, telephone, footboard, wardrobe, blind, hotel_room-s, eiderdown
32. river, embankment, pier, footbridge, lake, ship, bridge-s, deck, island, brushes, harbor-s, restaurant_patio-s, mill, cabin, pavilion, structure, dam, fountain-s, dam-s, canal-urban-s, lift_bridge-s, village, industrial_area-s, ice_skating_rink-outdoor-s, lido_deck-outdoor-s, parking lot, trestle, quay, aquatic_theater-s, lake-artificial-s, shipyard, shore
33. road, car, sidewalk, signboard, street-s, streetlight, handle, headlight, license plate, ashcan, roof, rim, taillight, balcony, windshield, van, bannister, pipe, air conditioner, bumper
34. sink, faucet, bathroom-s, towel, bathtub, toilet, countertop, lid, jar, water tank, toilet tissue, screen door, shower, soap dispenser, tap, towel rack, shower stall, bidet
35. plate, bowl, drinking glass, napkin, knife, fork, spoon, dining_car-s
36. person, arm, hand, hair, mouth, foot, eyebrow
37. spotlight, stage, silver screen, grand piano, mezzanine, auditorium-s, podium, theater-indoor_procenium-s, movie_theater-indoor-s, stage-indoor-s, conference_center-s, wrestling_ring-indoor-s, choir_loft-exterior-s
38. stove, work surface, kitchen-s, oven, refrigerator, microwave, exhaust hood, button panel, dishwasher, fruit, coffee maker, pitcher, kitchen island, kettle, teapot, dishrag, paper towel, canister, saucepan
39. tent, cart, amusement_park-s, playground-s, playground, pool, slide, roller coaster, sun_deck-s, sandbox, big top, circus_tent-outdoor-s
40. sky, tree, building, grass, ground, pole, fence
41. rope, horse, snow, pack, sheep, cow, hoof, horn, camera, cage, museum-indoor-s, tire, straw, horse-drawn carriage, plastic, parasol, firing_range-outdoor-s, natural_history_museum-s, elephant
42. wheel, bicycle, saddle, handle bar, chain wheel
43. bar, piano, bar-s, casino-indoor-s, slot machine, fast-food_restaurant-s, restaurant-s, television camera, organ, synthesizer, inn-indoor-s, television_studio-s, drum, fire, jewelry_shop-s, temple-east_asia-s, stalls, coffee_shop-s, barbershop-s, temple, dining_hall-s, cardroom-s, bistro-indoor-s
44. statue, cross, altar, shaft, capital, barrel, vault, pulpit, cathedral-indoor-s, church-indoor-s, altarpiece, cloister-indoor-s, wine_cellar-barrel_storage-s, pulpit-s, sacristy-s, mosque-indoor-s, apse-indoor-s, baptistry-indoor-s, chapel-s, baptismal font
45. chandelier, dining_room-s, candlestick, doorframe, candle, vent, stretcher, buffet, console table, place mat, bouquet, parlor-s, candelabrum, lobby-s, plinth, dinette-home-s, table cloth, hotel_breakfast_area-s
46. dotted, knitted, porous, pitted, perforated, crosshatched, polka-dotted, studded, flecked, scaly, waffled, honeycombed, chequered
47. forest-broadleaf-s, park-s, waterfall, forest-needleleaf-s, creek-s, greenhouse-indoor-s, leaves, leaf, forest_path-s, pond, yard-s, waterfall-fan-s, campsite-s, forest_road-s, trellis, botanical_garden-s, rope_bridge-s, mountain_path-s, dolmen-s, vegetable_garden-s, irrigation_ditch-s, orchard-s, waterfall-cascade-s, herb_garden-s, topiary_garden-s, cottage_garden-s, canal-natural-s, formal_garden-s, zen_garden-s, fishpond-s, moat-dry-s, hedge_maze-s, flight_of_stairs-natural-s, drainage_ditch-s, japanese_garden-s
48. gas pump, gas_station-s, weighbridge-s, weighbridge, service station, box office, caravan, recycling bin, bus_depot-outdoor-s, airport-entrance-s, motel-s, kiosk-outdoor-s, convenience_store-outdoor-s, movie_theater-outdoor-s, manufactured_home-s, industrial_park-s, bank-indoor-s, parking_garage-outdoor-s, library-outdoor-s, liquor_store-outdoor-s, loading_dock-s, museum-outdoor-s, newsstand-outdoor-s, hangar-outdoor-s, toll booth
49. rock, bush, hill, animal, dirt track, decoration, bell, fire escape, construction_site-s, planks, slum-s, village-s, shanties, medina-s, fire_escape-s, bulldozer, steam shovel, excavator, excavation-s, rubble, crate,

rubble-s

50. stairway, gate, conveyer belt, escalator, baggage_claim-s, tunnel, subway_station-corridor-s, escalator-indoor-s, subway_station-platform-s, escalator-outdoor-s
51. wall socket, wallpaper, skirt, canopy, stile, bookcase, beam, grill, backplate, muntin, heater, sash, blade, chest, lower sash, upper sash, spindle, attic-s, side rail, deck chair, skylight, casing, sill, tapestry, rocking chair, earmuffs, radio, folding screen, blinds
52. bag, rubber, menu, balloon, martial_arts_gym-s, hand cart, auto_mechanics-indoor-s, ticket window
53. wood, painted, fabric, glass
54. board, blackboard, file cabinet, classroom-s, scale, boot, playroom-s, map, gym shoe, toyshop-s, kindergarden_classroom-s, aquarium, table game, day_care_center-s, pictures, binder, sewing machine, kiosk-indoor-s, booth-indoor-s, hat_shop-s, pigeonhole, checkout_counter-s, tearoom-s, canteen-s, vegetables
55. dinette-vehicle-s, galley-s, rudder, pilothouse-indoor-s, hunting_lodge-indoor-s
56. blotchy, bumpy, smeared, sprinkled, stained, frilly, freckled, crystalline, bubbly
57. shelves, bedclothes, wire, mat
58. machine, tank, streetcar, equipment, beauty_salon-s, gymnasium-indoor-s, workbench, dentists_office-s, hospital_room-s, operating_room-s, machinery, dental chair, set of instruments, assembly_line-s, workshop-s, call_center-s, clean_room-s, cheese_factory-s
59. earth, stairs, house, path
60. interlaced, spiralled, swirly, braided, paisley, amphitheater-s, labyrinth-indoor-s, labyrinth-outdoor-s, labyrinth
61. mountain, water, boat, sea, sand, land
62. wall, floor, windowpane, door, ceiling, table, chair, painting, cabinet, light, curtain, sofa, box
63. bench, hot tub, jacuzzi-indoor-s, bullring-s, jacuzzi-outdoor-s, manhole-s, bullring, terraces
64. cockpit-s, controls, bus_interior-s, steering wheel, auto_showroom-s, windscreen, airplane_cabin-s, instrument panel, dashboard, telescope, car_interior-backseat-s, meter, control_tower-indoor-s, limousine_interior-s
65. bucket, washer, utility_room-s, laundromat-s, tumble dryer, washing machines
66. column, top, seat cushion, coffee table, living_room-s, leather, television, back pillow, seat base, inside arm, tray, fireplace, outside arm, apron, ottoman, blanket, arm panel
67. hovel, garage door, house-s, patio, gazebo-exterior-s, porch, carport, shelter, driveway-s, campus-s, cabin-outdoor-s, greenhouse, barn-s, hen, hunting_lodge-outdoor-s, chicken_coop-outdoor-s, outhouse-outdoor-s, garage-outdoor-s, henhouse, shed, dacha-s, covered_bridge-exterior-s, water wheel, gravel, carport-outdoor-s, kennel-outdoor-s, boathouse-s, greenhouse-outdoor-s, oast_house-s, beach_house-s, chalet-s, guardhouse-s, hut-s, flight_of_stairs-urban-s, shed-s, water_mill-s, military_hut-s, granary-s, cottage-s, cabana-s, joss_house-s, lean-to-s, fort-s, covered bridge
68. shoe, apparel, hat, jacket, shirt, closet-s, trouser, sweater
69. brick, wicker, fur
70. bowling_alley-s, bowling alley, skittle alley
71. case
72. banded, striped, gauzy, lined, corridor-s, pleated, grooved, balcony-interior-s, bird cage, jail_cell-s, shower-s, lockers, locker_room-s, elevator-interior-s, kennel-indoor-s, grille door, fitting_room-exterior-s, fitting_room-interior-s, elevator-freight_elevator-s, elevator_shaft-s, cargo_container_interior-s, backstairs-s, bank_vault-s
73. black-c, brown-c, green-c, yellow-c, red-c, orange-c, awning
74. microphone, home_theater-s, berth-s, berth, oar, podium-indoor-s, dugout-s, witness_stand-s, witness stand
75. art_studio-s, guitar, easel, newspaper, dorm_room-s, drawing, jersey, subway_interior-s, art_school-s, canvas