Sematic Segmentation using Resource Efficient Deep Learning

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Introduction

Semantic segmentation

Divide an input image into different regions which contain a desired object or background.

Figure 1: Left: Input image; Right: Segmentation result.

Applications

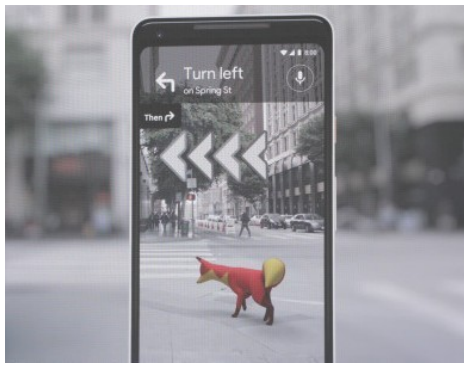
a Autonomous cars

b Robotics

c Augmented reality

(a) Street scene [1]

(b) Indoor scene [2]



(c) Augmented guide [3]

Dataset

Objects in the dataset

- First row from left: distance_tube, m20, bearing, axis, r20, m30, m20_100, motor, bearing_box_ax16, bearing_box_ax01, f20_20_B, f20_20_G.
- Second row from left: em_01, s40_40_B, s40_40_G, em_02, container_box_red, container_box_blue.

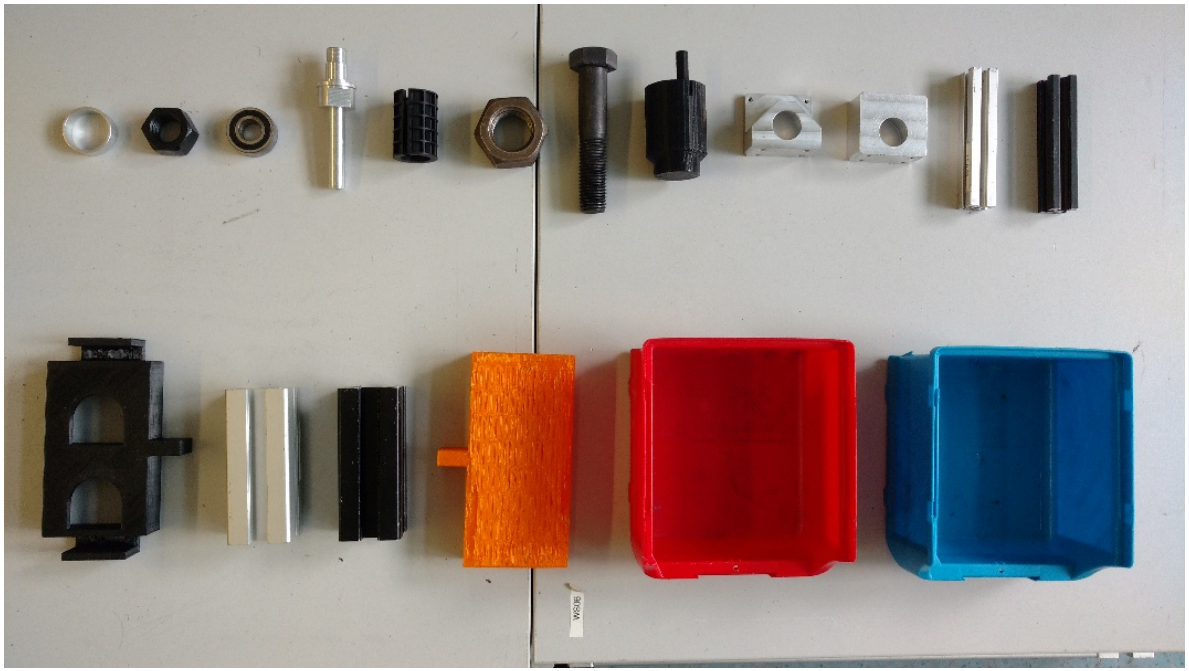


Figure 3: 18 objects in the dataset.

Annotation process

MATLAB ImageLabeler

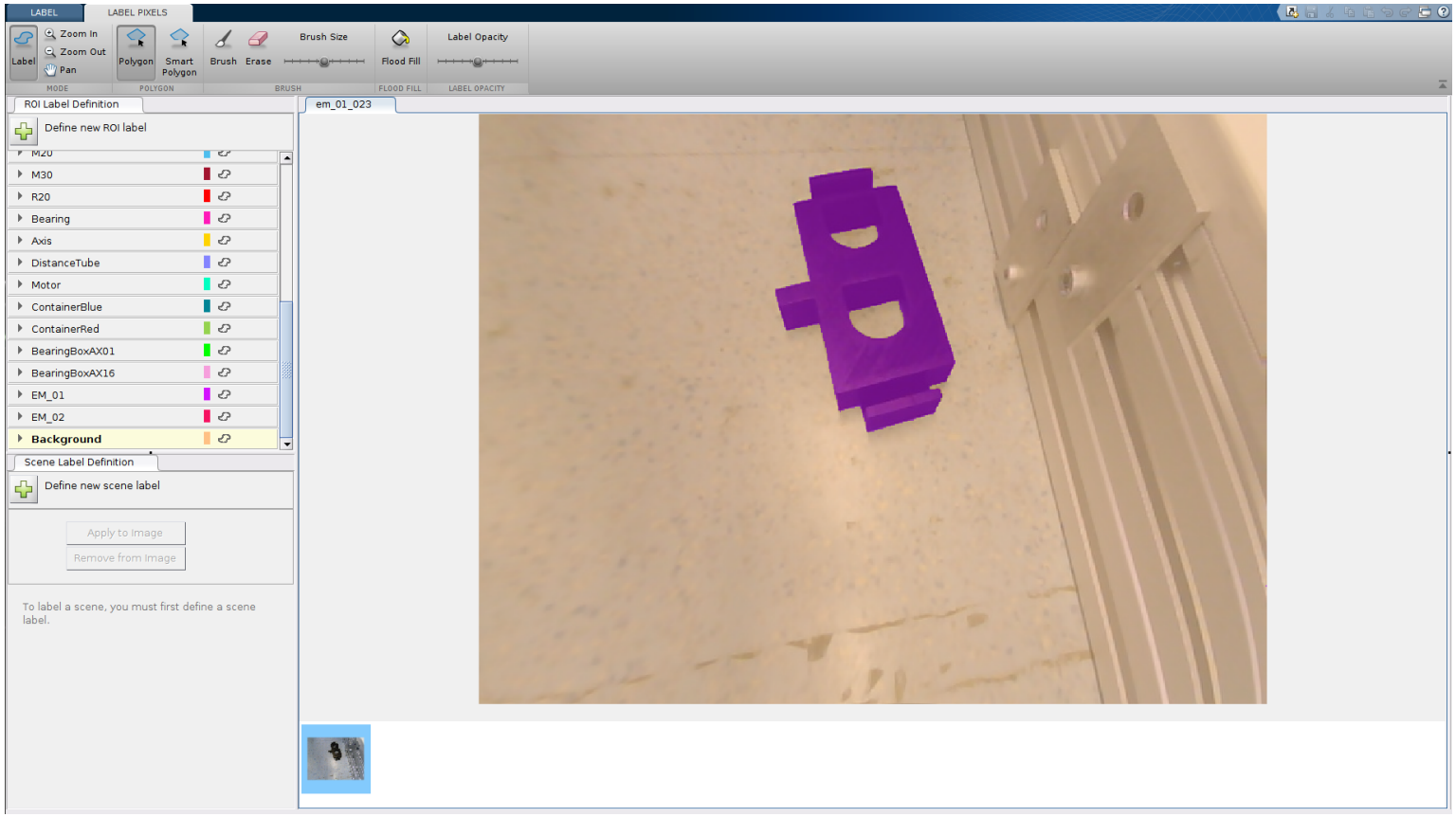


Figure 4: A sample object being labeled in ImageLabeler.

Artificial image generation

Motivation

- For an image containing 1 desired object, roughly 4 minutes was spent for manual annotation.
- Capturing diverse real-world variations is time consuming.

Process

- Collect RGB intensity values of objects using manual annotation.
- Create a list of all the collected objects.
- For an artificial image, select a background image and random objects from the list of objects.
- Place the selected objects at random locations and at random scales.
- Correspondingly generate semantic labels and object detection labels.

Artificial image generation

Sample result

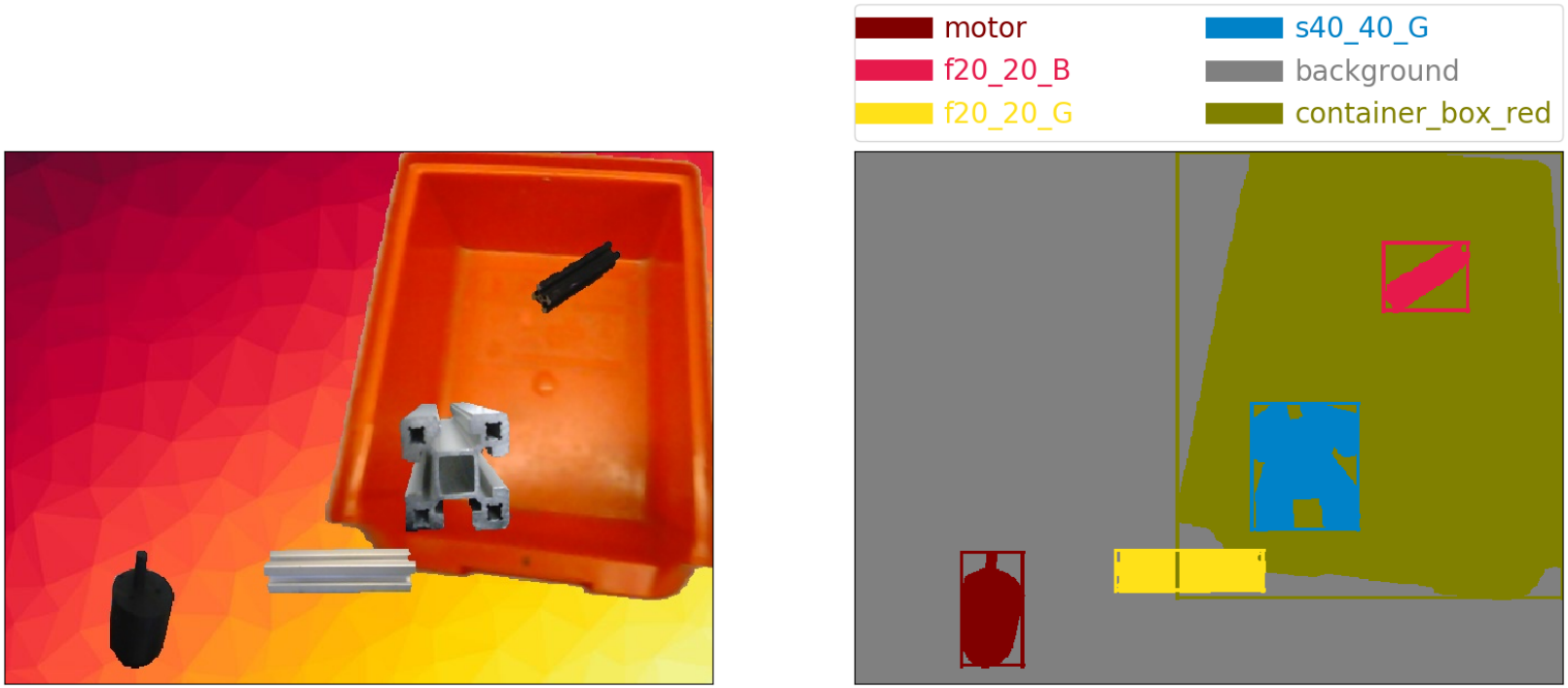


Figure 5: Sample results produced by the artificial image generation algorithm.

Dataset variants

Motivation

- Inability to distinguish size.

(a) m20

(b) m30

Figure 6: m30 is larger than m20

- Inability to distinguish shape.

(a) ax16

(b) ax01

(c) ax16

(d) ax01

Figure 7: Bearing_box ax16 and ax01 are distinguishable from similar viewpoints (a) and (b) but are indistinguishable from similar viewpoints (c) and (d).

Dataset variants

Number of classes

Variant	Number of classes including background
atWork_full	19
atWork_size_invariant	15
atWork_similar_shapes	13
atWork_binary	2

Table 1: Number of classes in dataset variants.

Number of images

	Training	Validation	Test
Real Images	396	72	69
Artificial Images	7104	870	870
Total Images	7500	942	939

Table 2: Number of images in the dataset.

Dataset analysis

- Percentage of pixels of an object $= \frac{NP_o}{NP_s}$.
  NP_o = Number of pixels occupied by the object in the training set.
  NP_s = Total number of pixels in the training set.

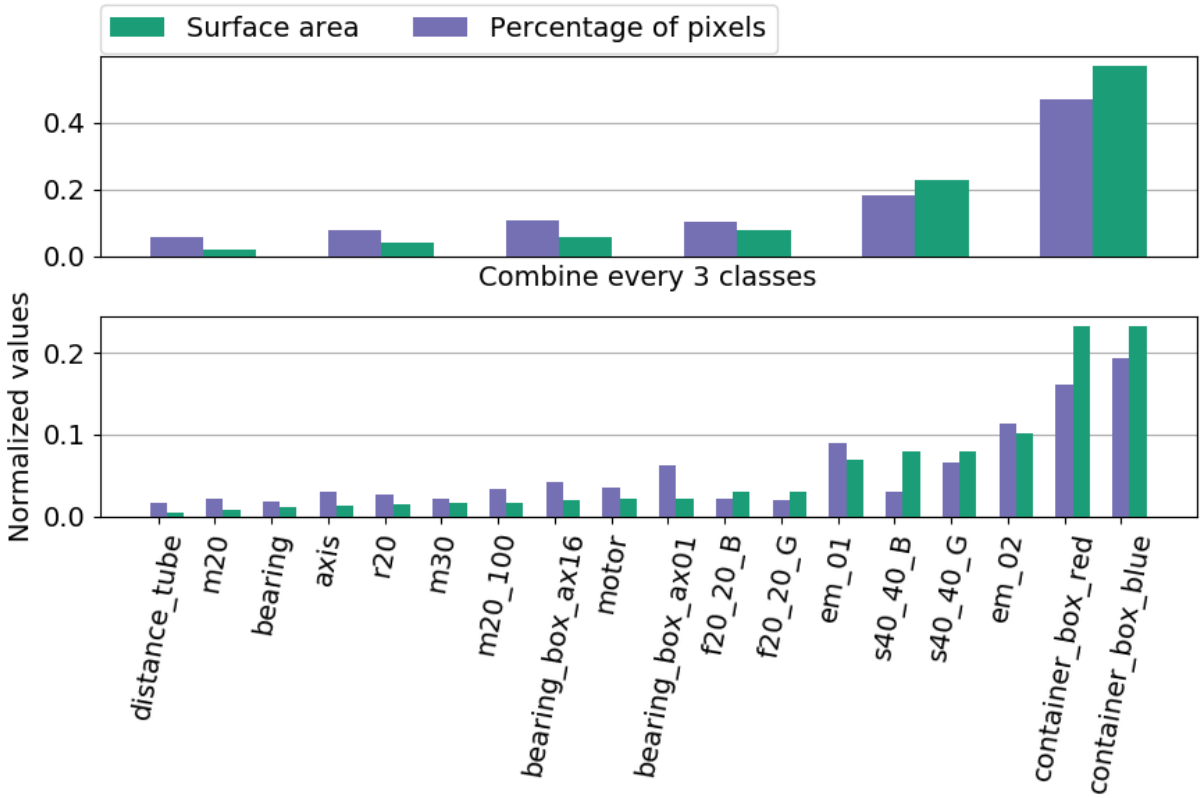


Figure 8: Percentage of pixels vs corresponding real-world surface area

Architecture of DeepLabv3+

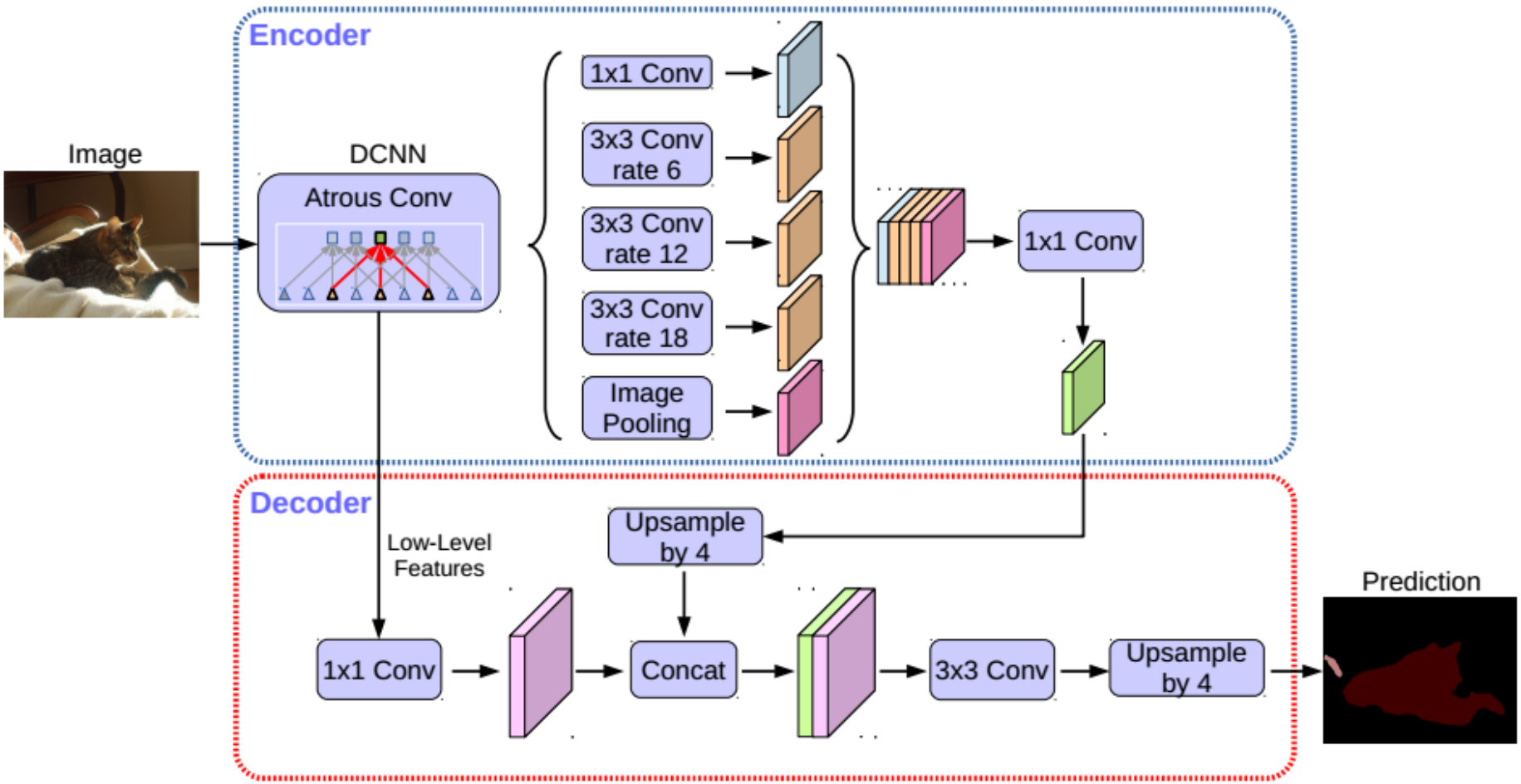


Figure 9: An illustration of DeepLabv3+ architecture. The encoder extracts features at different scales and the decoder refines object boundary delineation.

Depthwise seperable convolutions

- First depthwise convolution, then pointwise convolution.
- Row 2 to row 5: depthwise convolution, 6th row: pointwise convolution.

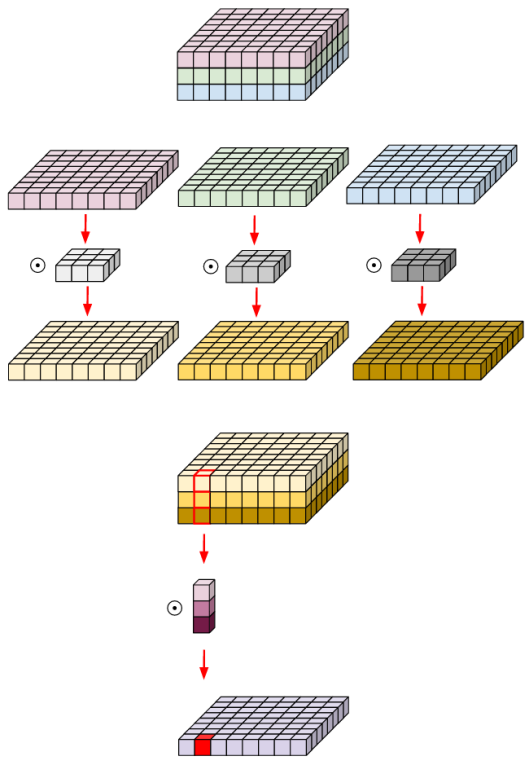


Figure 10: Depthwise seperable convolution.

MobileNetv2 encoder of DeepLabv3+

- Depthwise seperable convolutions.
- Inverted residual with linear bottleneck.

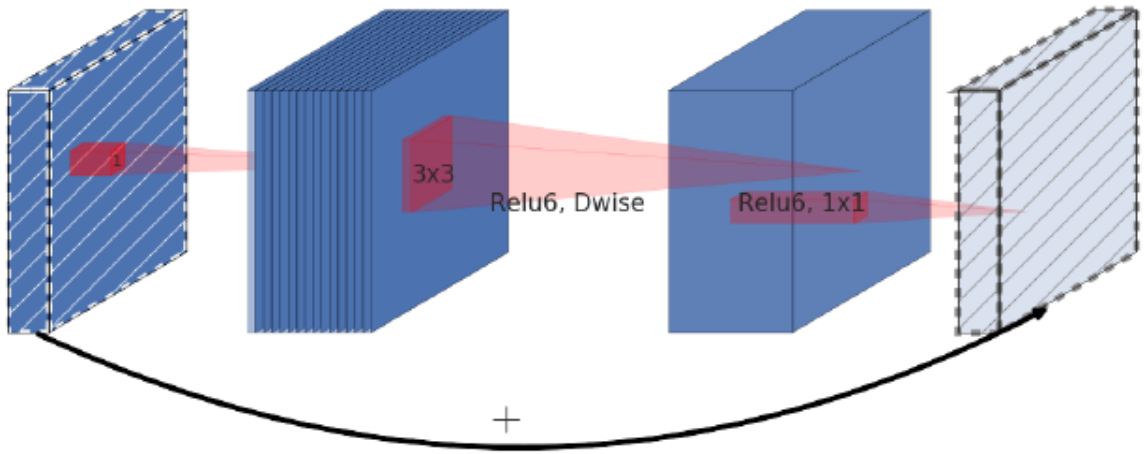


Figure 11: Inverted residual block

Xception encoder of DeepLabv3+

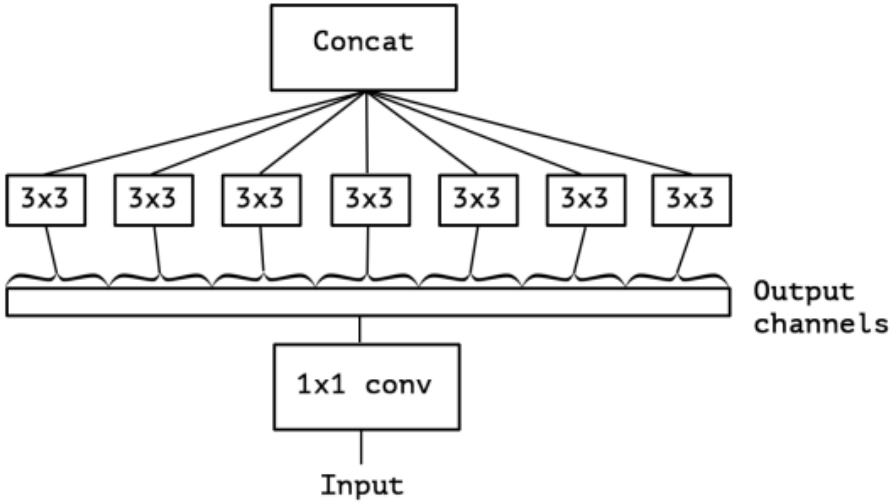


Figure 12: Xception module

Atrous separable convolutions

Comparing encoders

- Per class IOU $= \frac{ground\_truth \cap prediction}{ground\_truth \cup prediction}$
- mIOU = mean of all class IOUs.
- DeepLabv3+ with Xception encoder achieves higher mIOU on all four dataset variants.

Dataset variant	**mIOU in %**	
	MobileNetv2	Xception
atWork_full	77.47	89.63
atWork_size_invariant	83.10	92.47
atWork_similar_shapes	82.10	90.71
atWork_binary	96.06	98.68

Table 3: This table lists the mIOU obtained by DeepLabv3+ with MobileNetv2 and Xception encoders on 4 dataset variants.

Comparing dataset variants

- Background/foreground segmentation leads to the highest mIOU.
- Treating all objects as different classes leads to the lowest mIOU.
- Combining objects similar in shape, size or color improves mIOU.

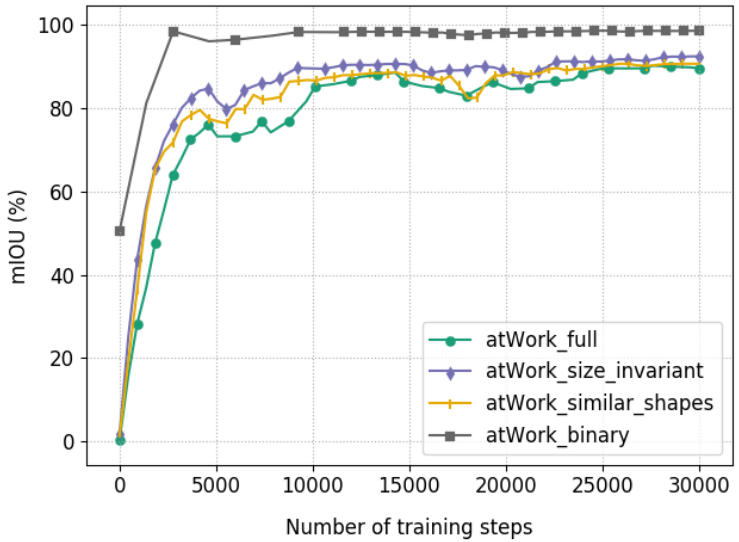


Figure 13: mIOU (%) vs Number of training steps
DeepLabv3+ with Xception encoder on all dataset variants

Comparing individual classes

- 9.88 % of pixels belonging to m30 is classified as m20.
- 9.97 % of pixels belonging to bearing box ax16 is classified as bearing box ax01 [Slide 9].

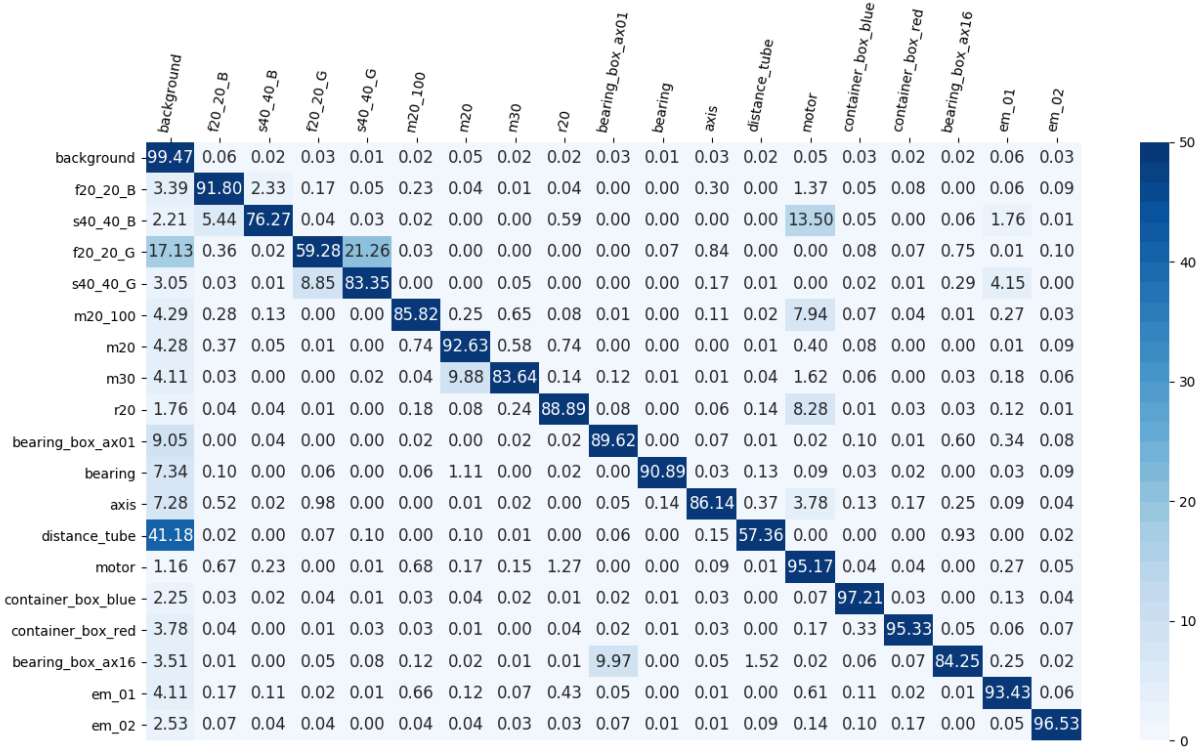


Figure 14: Confusion matrix on atWork_full dataset variant by DeepLabv3+ with MobileNetv2 encoder.

Comparing individual classes

- Class IOU shows an increasing trend with increase in Percentage of pixels.
- Percentage of pixels is shown to increase with surface area [Slide 11]. item DeepLabv3+ tends to learn larger objects first.

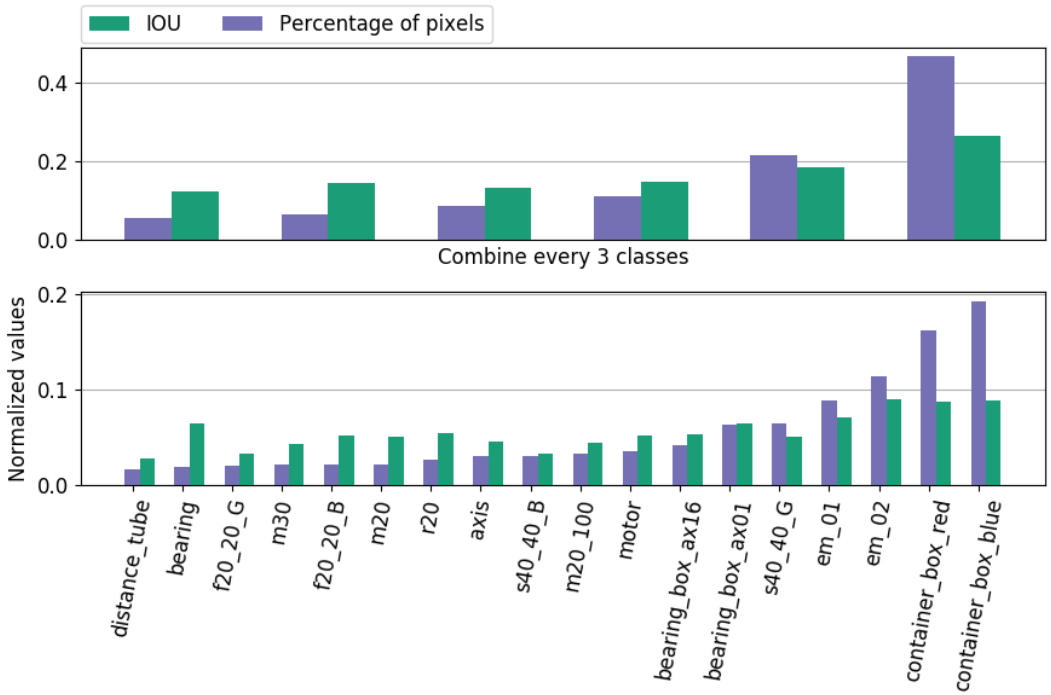


Figure 15: Individual class IOUs achieved by DeepLabv3+ with MobileNetv2 encoder is plotted with the percentage of pixels.

Quantizing the inference graph

- The inference graph is quantized.
- With MobileNetv2 encoder, 67 % drop in occupied disk memory is achieved. Drop in mIOU is around 9 %.
- With Xception encoder, 73 % drop in occupied disk memory is achieved. Drop in mIOU is around 2 %.

Quantizing the inference graph

Encoder	mIOU (%)	Number of parameters	FLOPS	Disk memory (MB)
MobileNetv2	84.66	2.11M	6.41B	8.7
MobileNetv2-8	75.17	2.11M	328.87M	2.8
Xception	92.42	41.05M	126.27B	165.6
Xception-8	90.4	41.05M	1.94B	44.7

Table 4: This table summarizes the average mIOU across all four dataset variants, number of parameters, and floating point operations (FLOPS) of both the quantized and full precision encoders of DeepLabv3+. "M" denotes million and "B" denotes billion.

Conclusion and future work

Contributions

- Artificial image generation algorithm.
- Segmentation dataset with 18 atWork objects.
- Evaluation of DeepLabv3+ with resource efficient encoders MobileNetv2 and Xception.

Future work

- Model interpretability.
- Architecture search.
- Fusion of 2D image data with point cloud information.

Thank you very much!

Are there any questions?

References

[1] C. dataset. Examples of fine annotations. Online accessed: 2018-08-03. URL: https://www.cityscapes-dataset.com/examples/#fine-annotations.

[2] N. Silberman. NYU Depth Dataset V2. Online accessed: 2018-08-03. URL: https://cs.nyu.edu/~silberman/datasets/nyu_depth_v2.html.

[3] S. Perez. Google makes the camera smarter with a Google Lens update, integration with Street View. Online accessed: 2018-08-03. URL: https://techcrunch.com/2018/05/08/google-makes-the-camera-smarter-with-a-google-lens-update-integration-with-street-view/?guccounter=1.