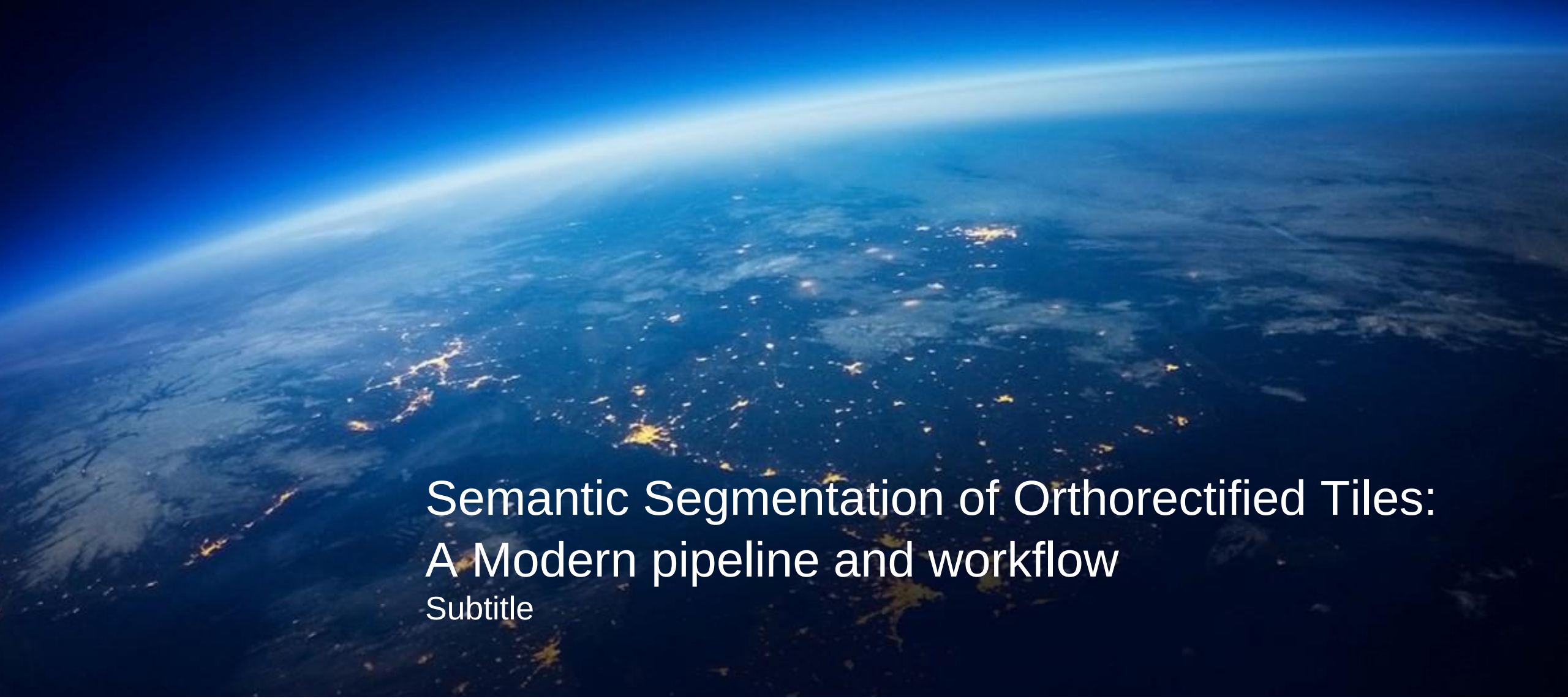


Semantic Segmentation of Orthorectified Tiles: A Modern pipeline and workflow

Subtitle

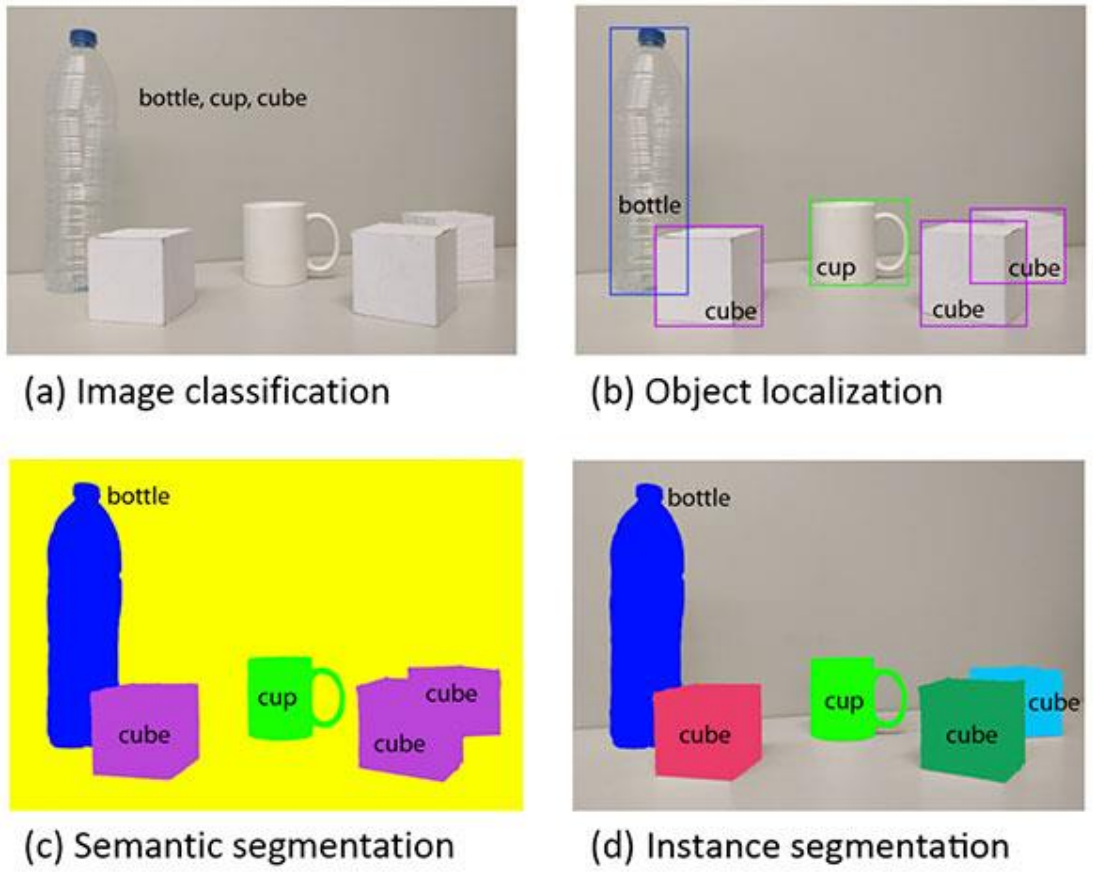
DEFENCE AND SPACE

Maher SEBAI – TIN3D

December 2019

AIRBUS

What is Semantic Segmentation in Deep Learning Context



 Source: https://arxiv.org/abs/1704.06857

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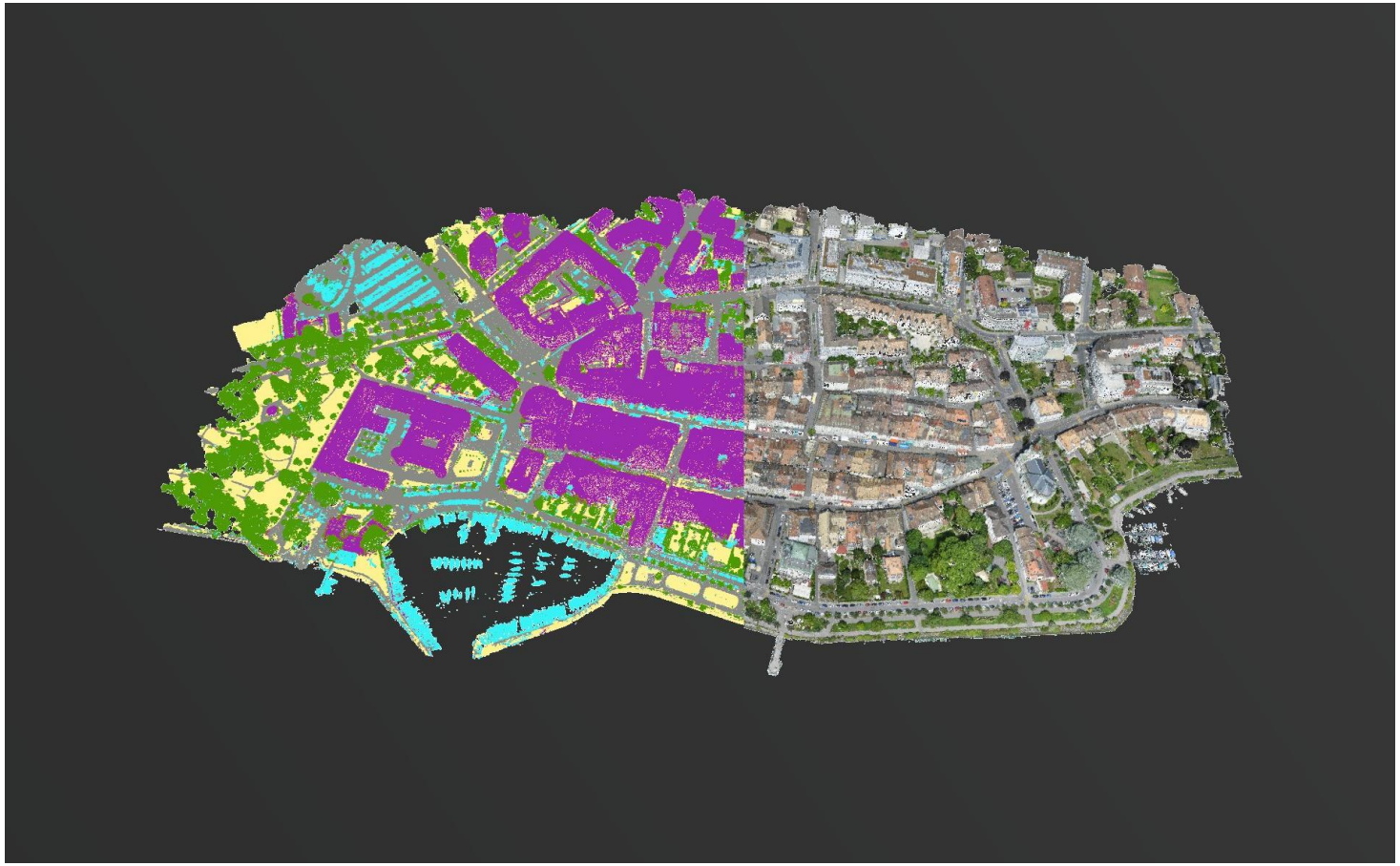
Smart 3D City: Potential Benefits

- Product added Value
  - Point Cloud Semantic
  - Urban planning
  - Statistics …

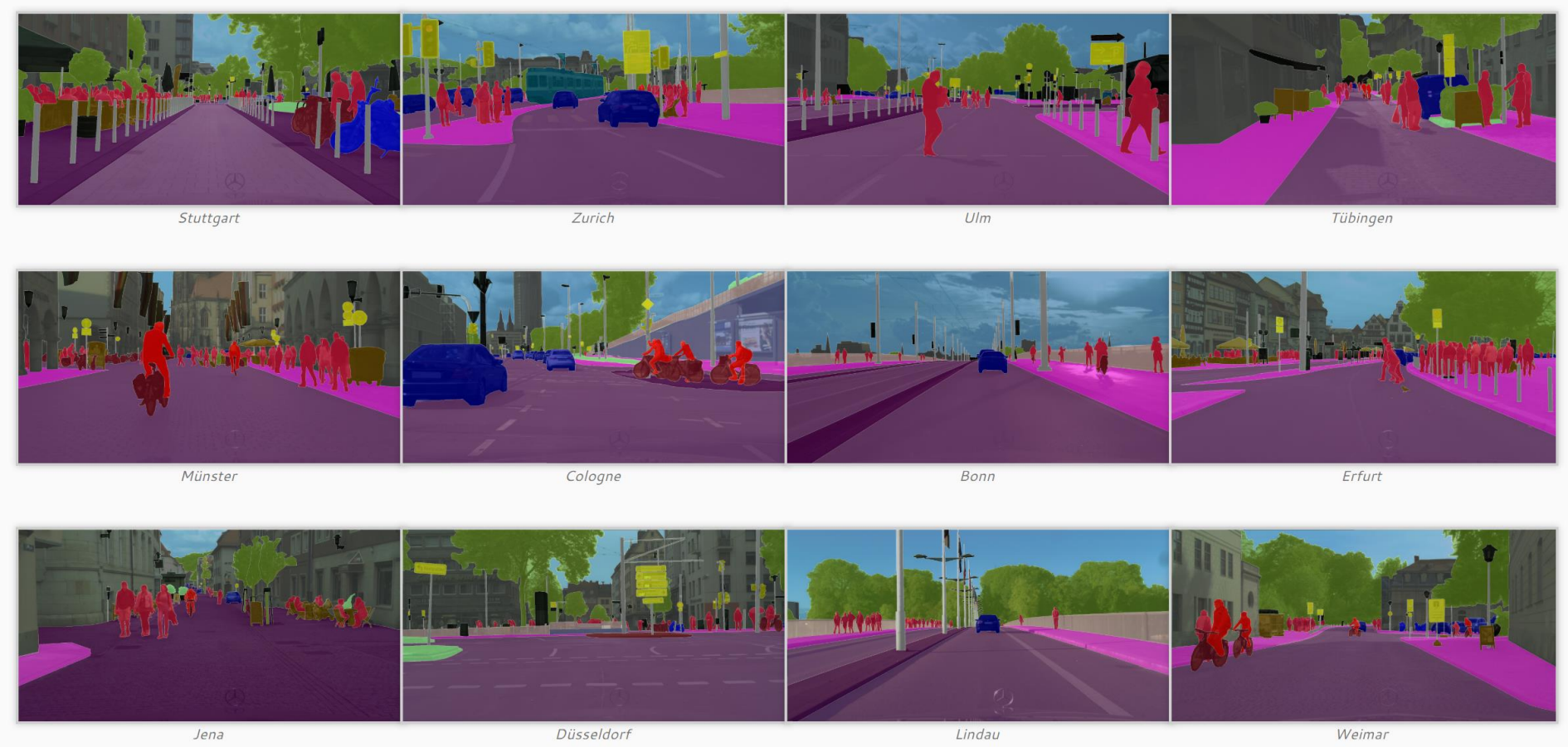


 Source: Pix4D

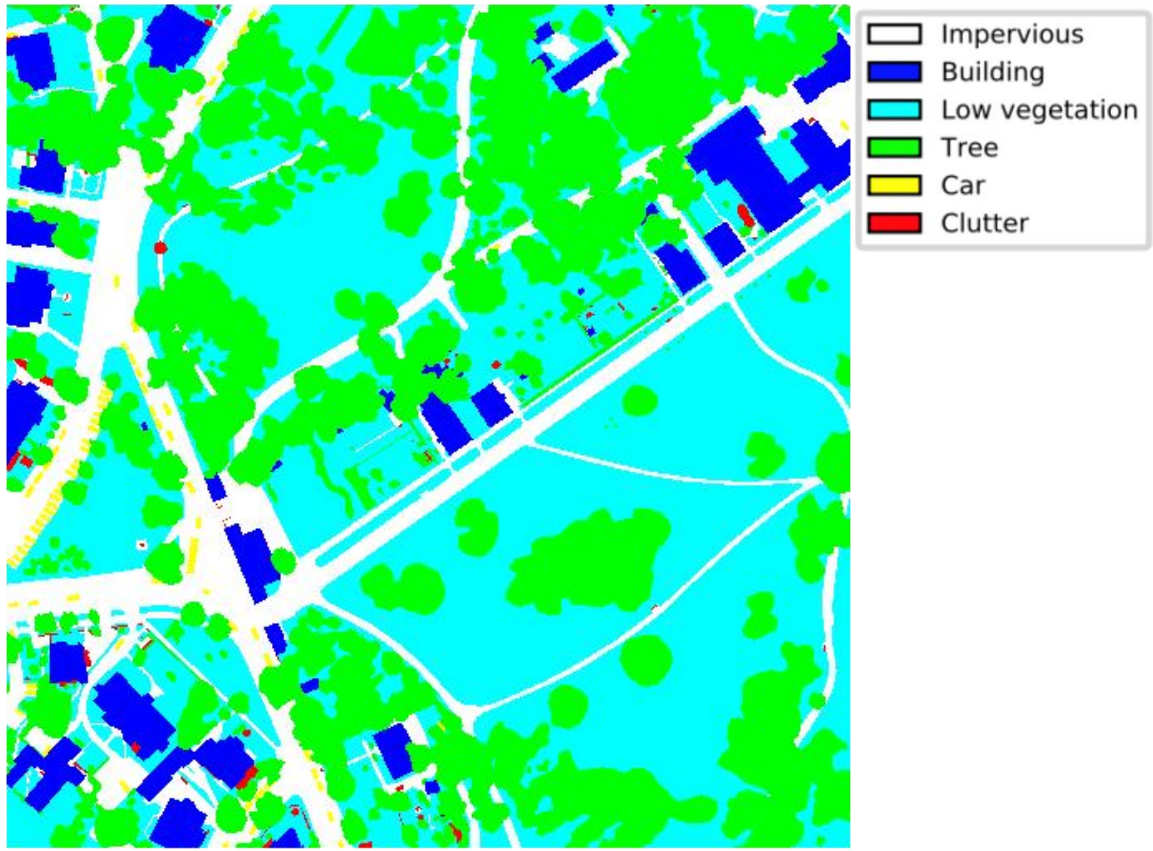
Supervised Semantic Segmentation Task Examples: MS COCO Dataset

 https://github.com/nightrome/cocostuff

Supervised Semantic Segmentation Task Examples: Cityscapes Dataset

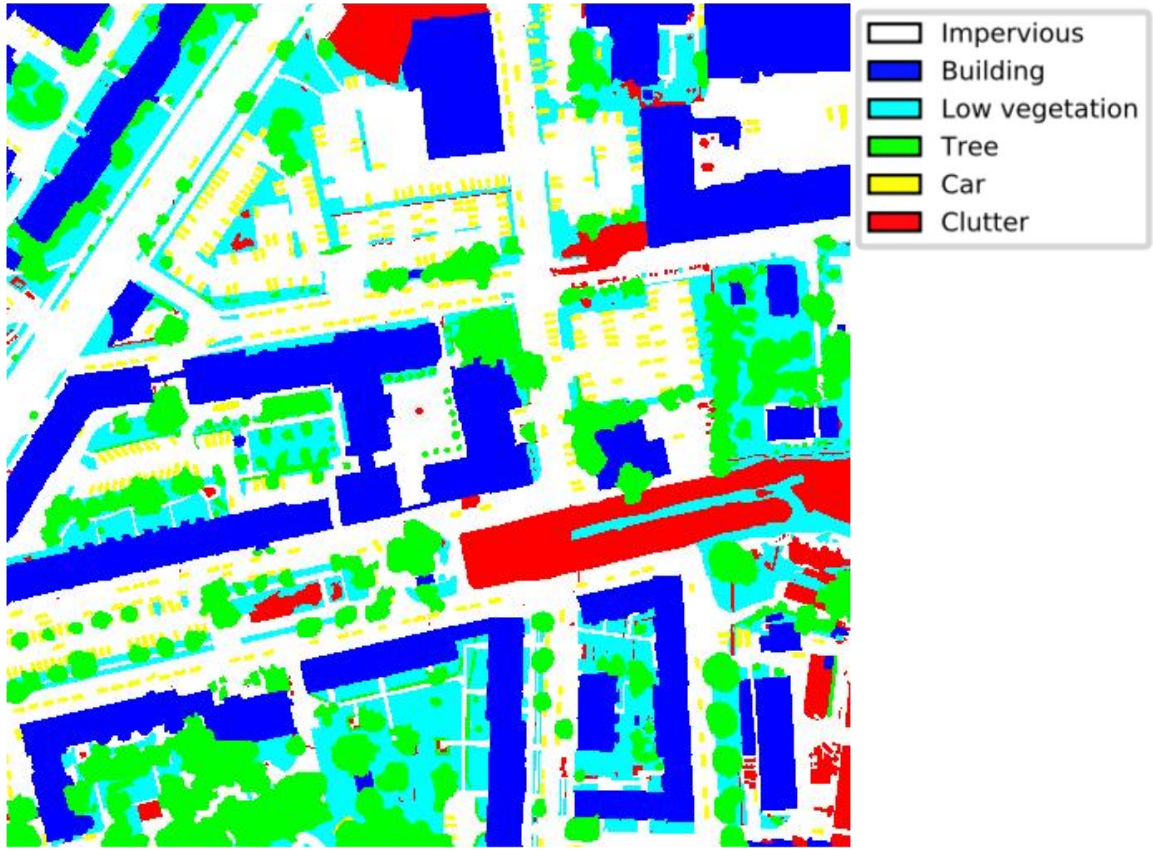


Supervised Semantic Segmentation Task Examples: ISPRS dataset (Potsdam)



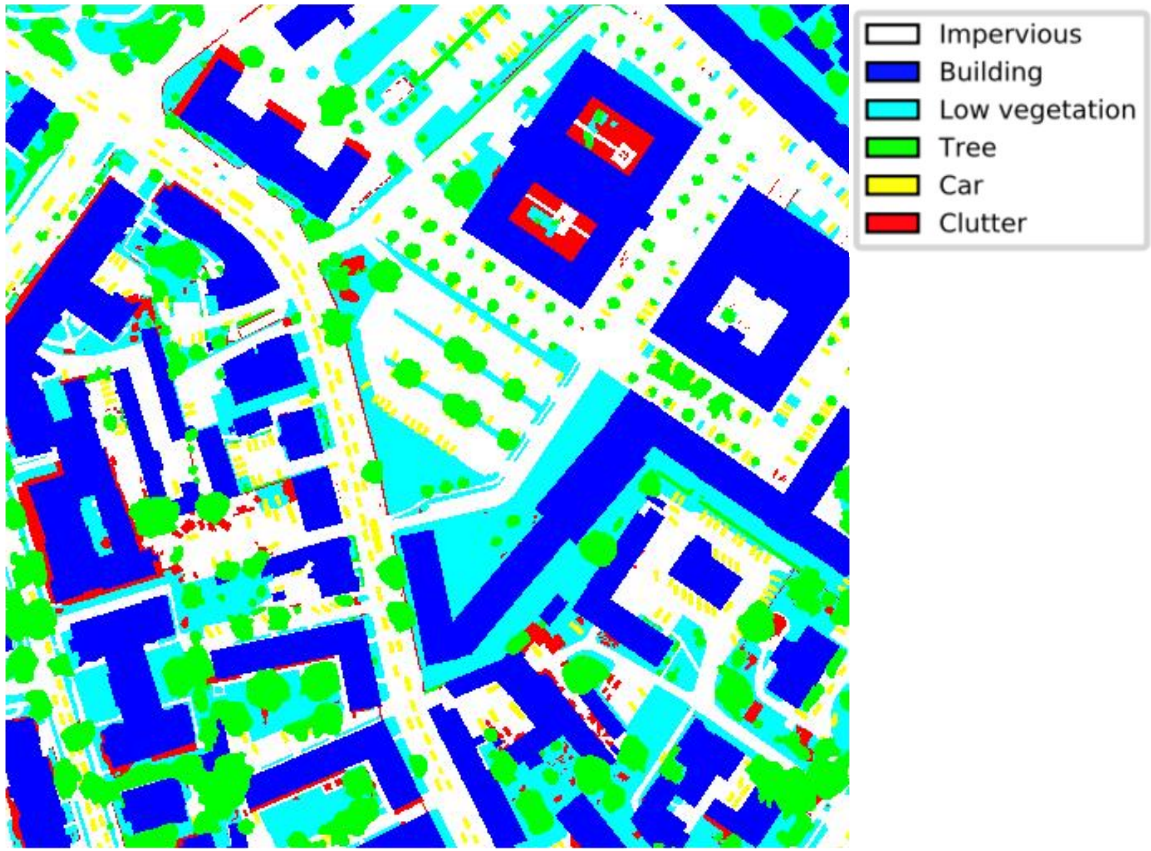
 http://www2.isprs.org/commissions/comm3/wg4/2d-sem-label-potsdam.html

Supervised Semantic Segmentation Task Examples: ISPRS dataset (Potsdam)



 http://www2.isprs.org/commissions/comm3/wg4/2d-sem-label-potsdam.html

Supervised Semantic Segmentation Task Examples: ISPRS dataset (Potsdam)



 http://www2.isprs.org/commissions/comm3/wg4/2d-sem-label-potsdam.html

ISPRS dataset details

Potsdam Benchmark dataset for ISPRS 2D Semantic labeling challenge in Potsdam:

- 38 tiles (6000x6000) at ≈ 5cm resolution
  - 24 Tiles dedicated for training
  - 14 Tiles for validation
- 4-bands IRRGB + DSM + NDSM
- Ground truth mask for 6 classes:
  - Building
  - Impervious Surfaces
  - Low Vegetation Tree
  - Tree
  - Car
  - Background

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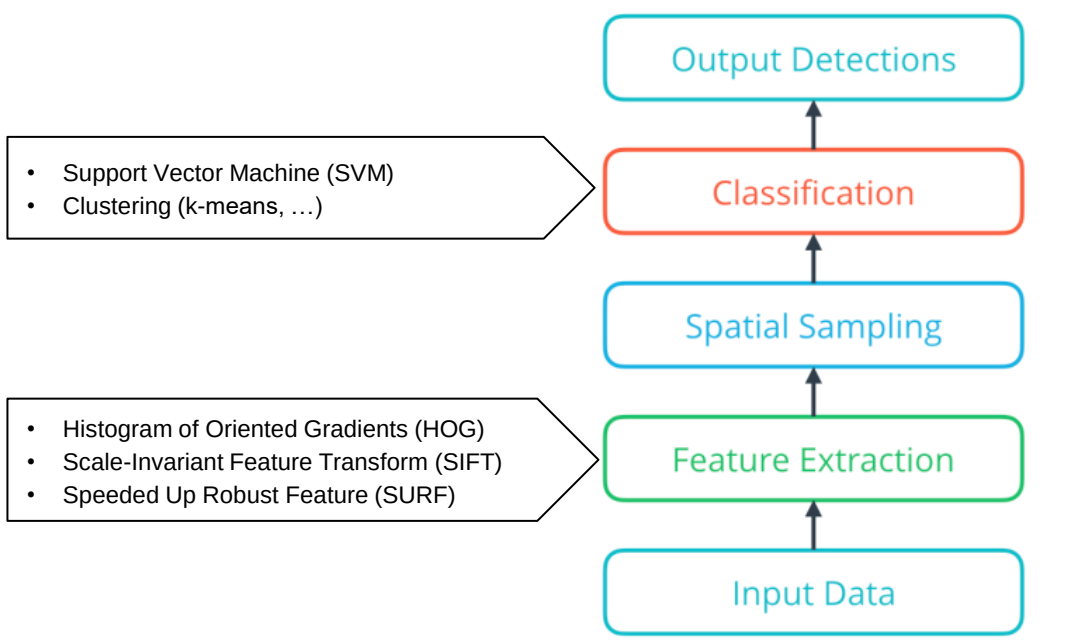
Development environment

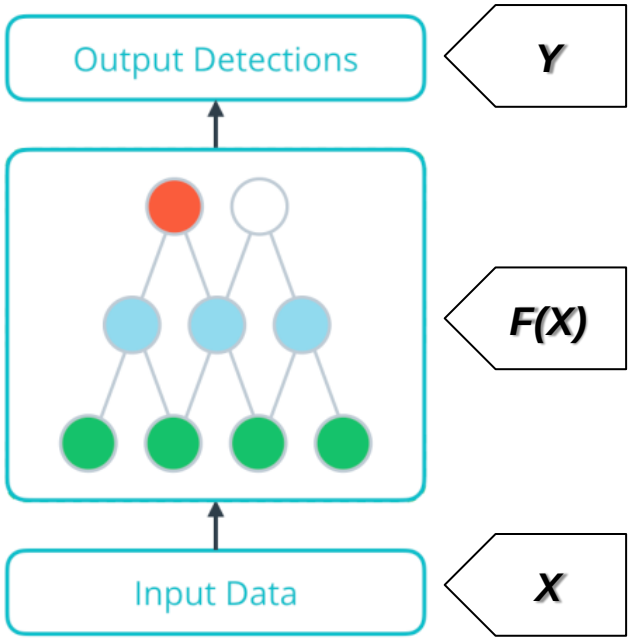
- Python 3.5
- Imageio 2.6
- Deep Learning Libraries:
  - Low-Level API: Tensorflow 2.0 (with eager_execution enabled)
  - High-Level API: Keras 2.2
  - Input pipeline API: Tensorflow.data
  - Monitoring API: TensorBoard

- Infrastructure:
  - 16-Core, 64GB RAM
  - Nvidia 16GB GPU (Tesla P100)
  - VM instance on GCP

Computer Vision Segmentation Approaches:



Traditional Computer Vision



Deep Neural Network

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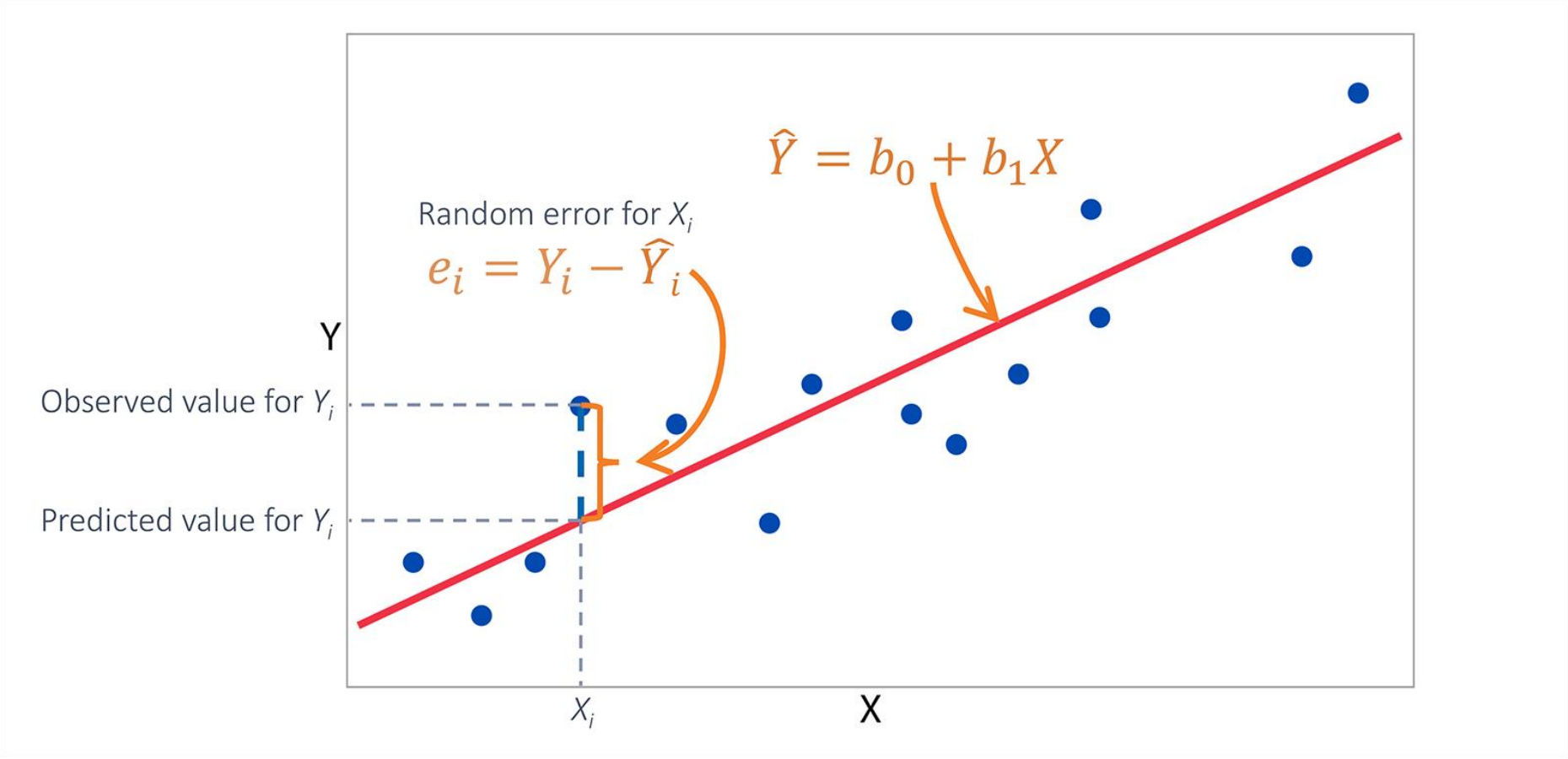
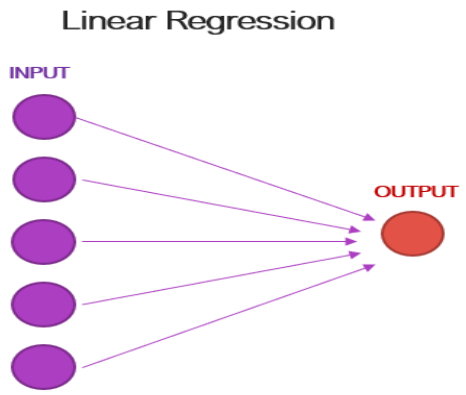
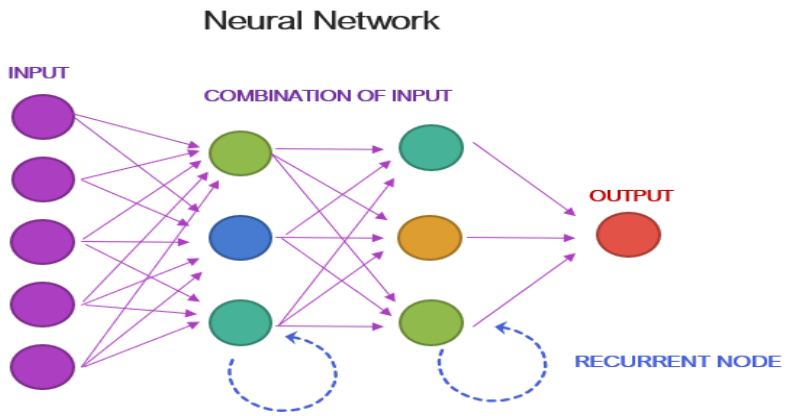
Parametric Modeling: Linear Regression



Linear Regression Vs Neural Networks:

	Linear Regression	Neural Networks
Supervised Learning	Explanatory variables X Response Variables Y	Input Aerial image Pixels X Reference Mask Pixels Y
Parametric Model	$Y = b_0 + b_1 X$	Pixel Label = $F(X\|W_1W_2W_3W_4\ldots)$
Minimizing Loss Function (Error)	Mean Squared Error	Cross-entropy
Optimization Algorithm	Analytical Solution	Gradient Descent
Goodness of fit Metrics	R^2, F-test, p-value …	Accuracy, Jaccard Index, …





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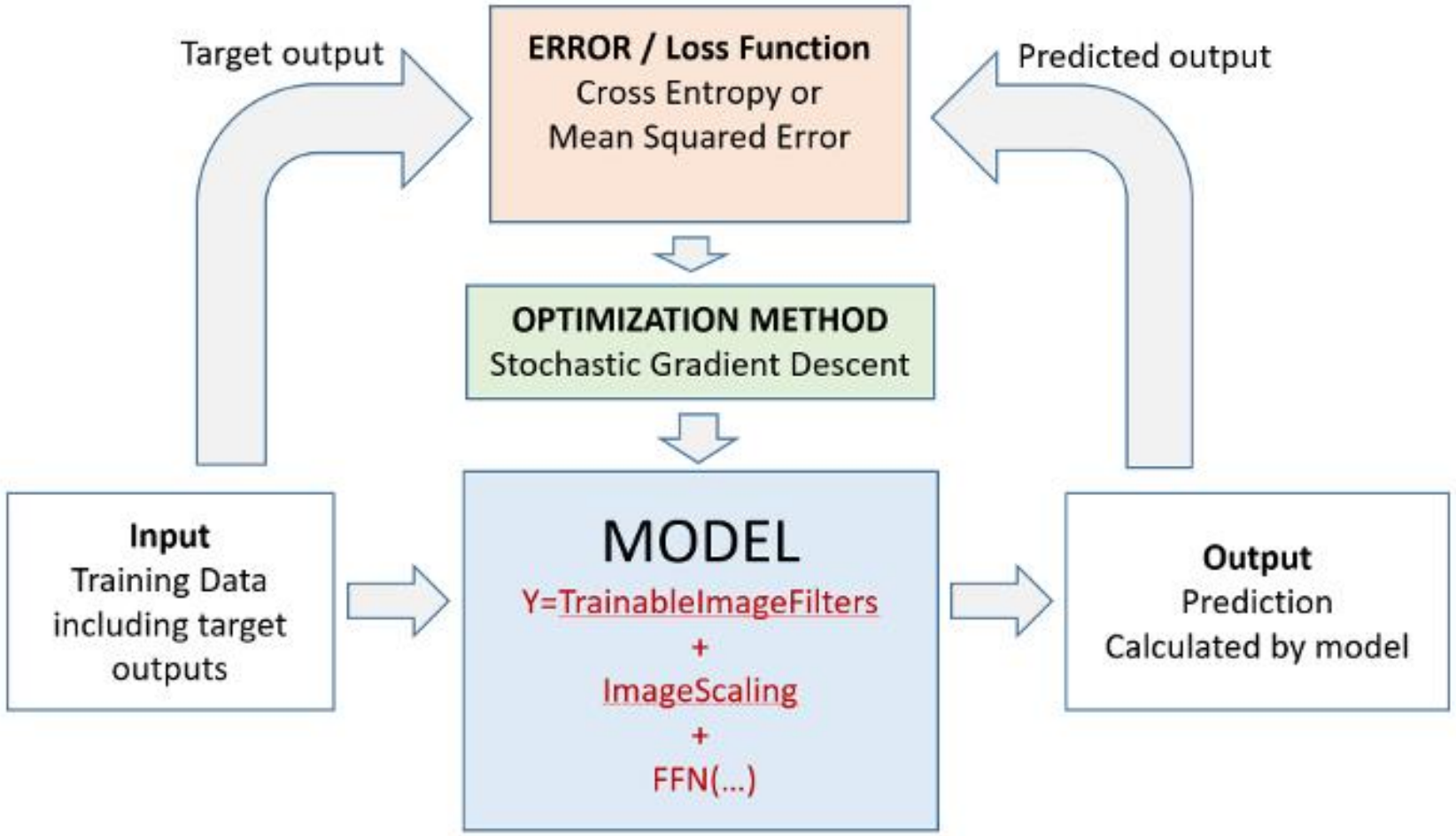
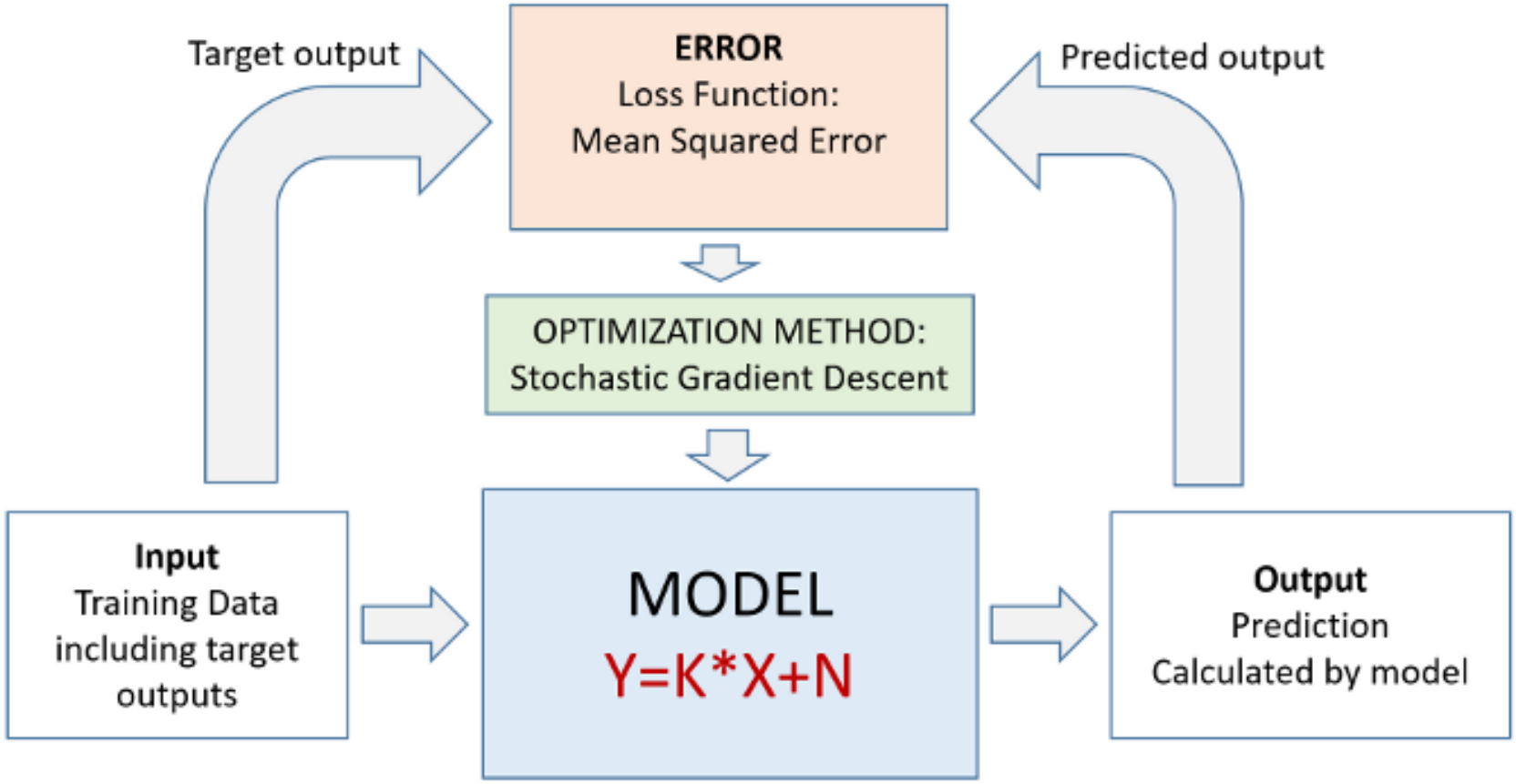
Neural Network Training Flowchart



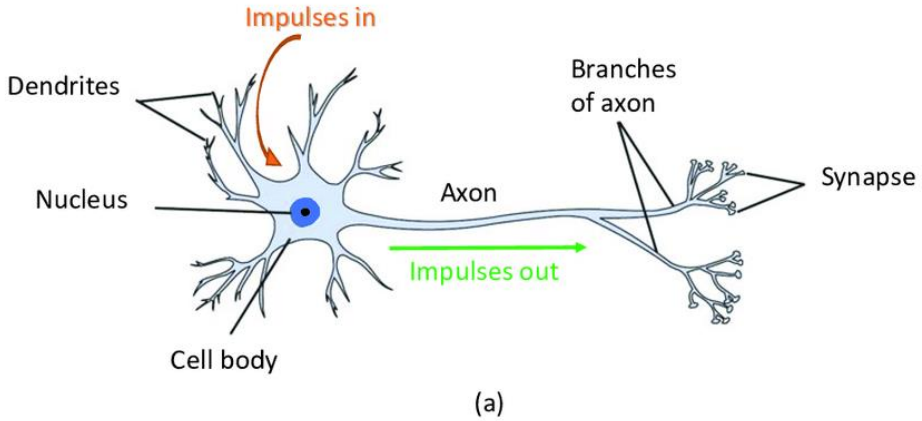
 http://www.deepnetts.com/blog/from-linear-regression-to-deep-learning-in-5-minutes.html

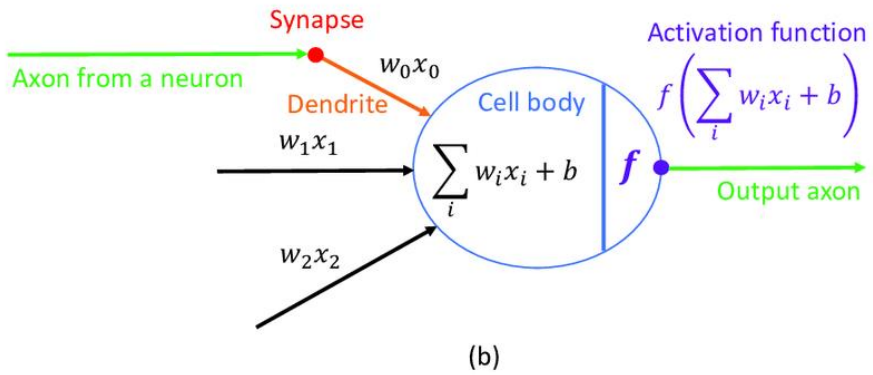
Linear Regression Training Flowchart:



 http://www.deepnetts.com/blog/from-linear-regression-to-deep-learning-in-5-minutes.html

Neural Networks Inspiration:

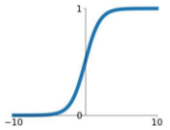




Activation Functions

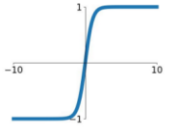
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



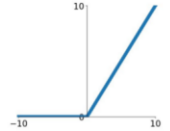
tanh

$\tanh(x)$



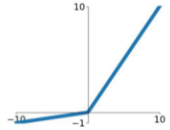
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

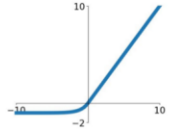


Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

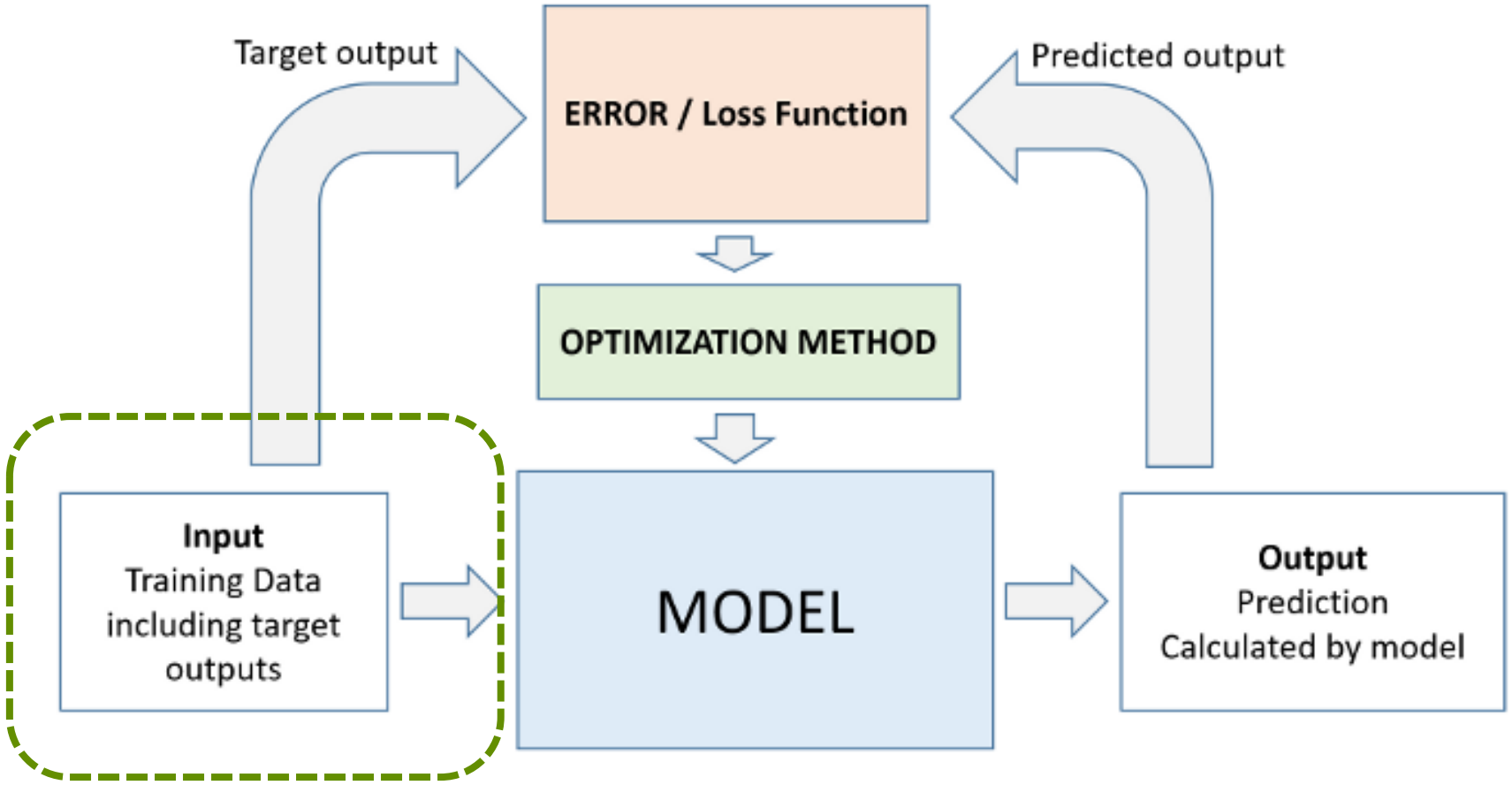
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



https://www.researchgate.net/figure/1-A-comparison-between-a-human-neuron-and-an-ANN-neuron-a-Shows-an-illustration-of-a_fig6_317679065

Input Pipeline: Tensorflow.data

Input Pipeline



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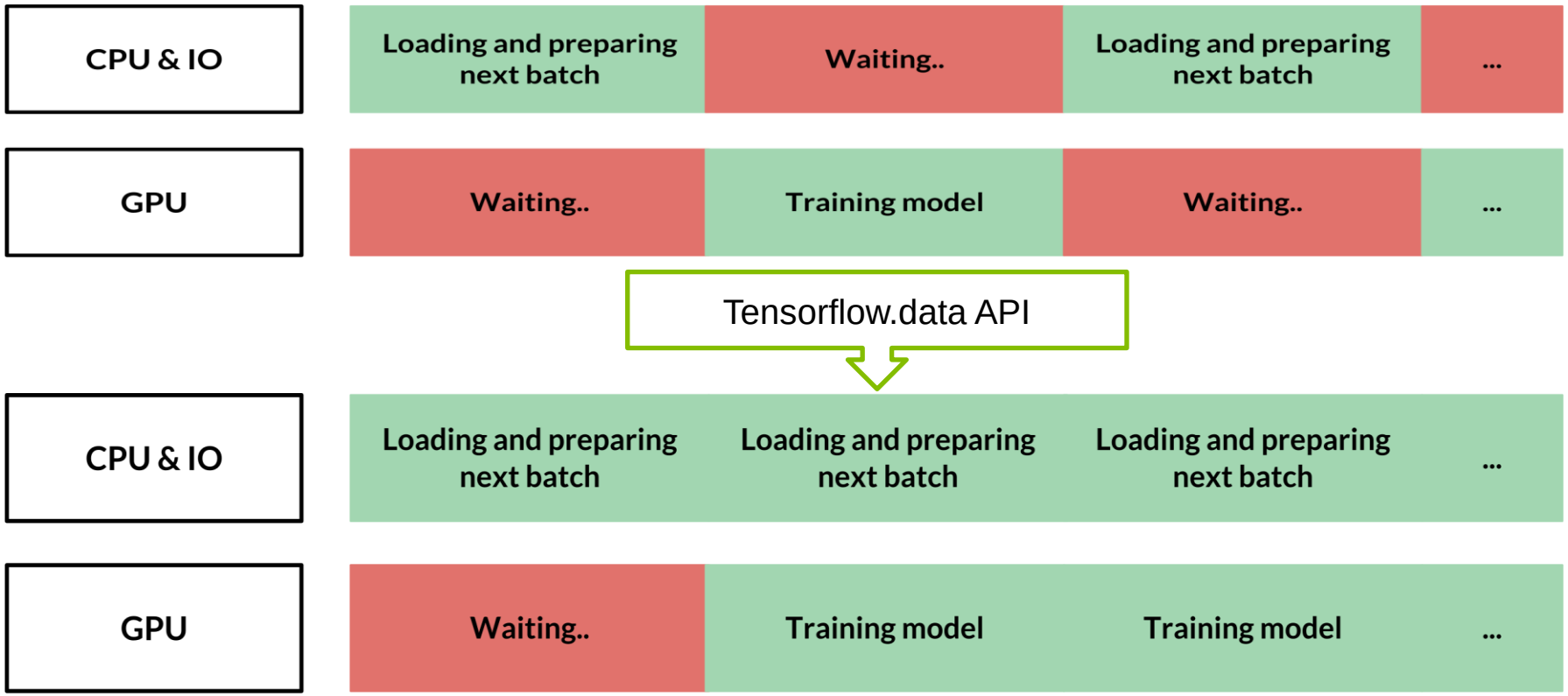
Terminology:

- Training Dataset: The dataset that is used to compute the Loss function gradient to update the Models weights
- Validation Dataset: The dataset that is used to compute the Generalization Performance of the Model (Metrics)
- Epoch: One Epoch is when an ENTIRE dataset is passed forward and backward through the neural network only ONCE.
- Batch size: Total number of training examples present in a single batch.
- Example: a dataset made of 100 images with Batch size of 20 images => 1 epoch consists of 5 Batch iterations

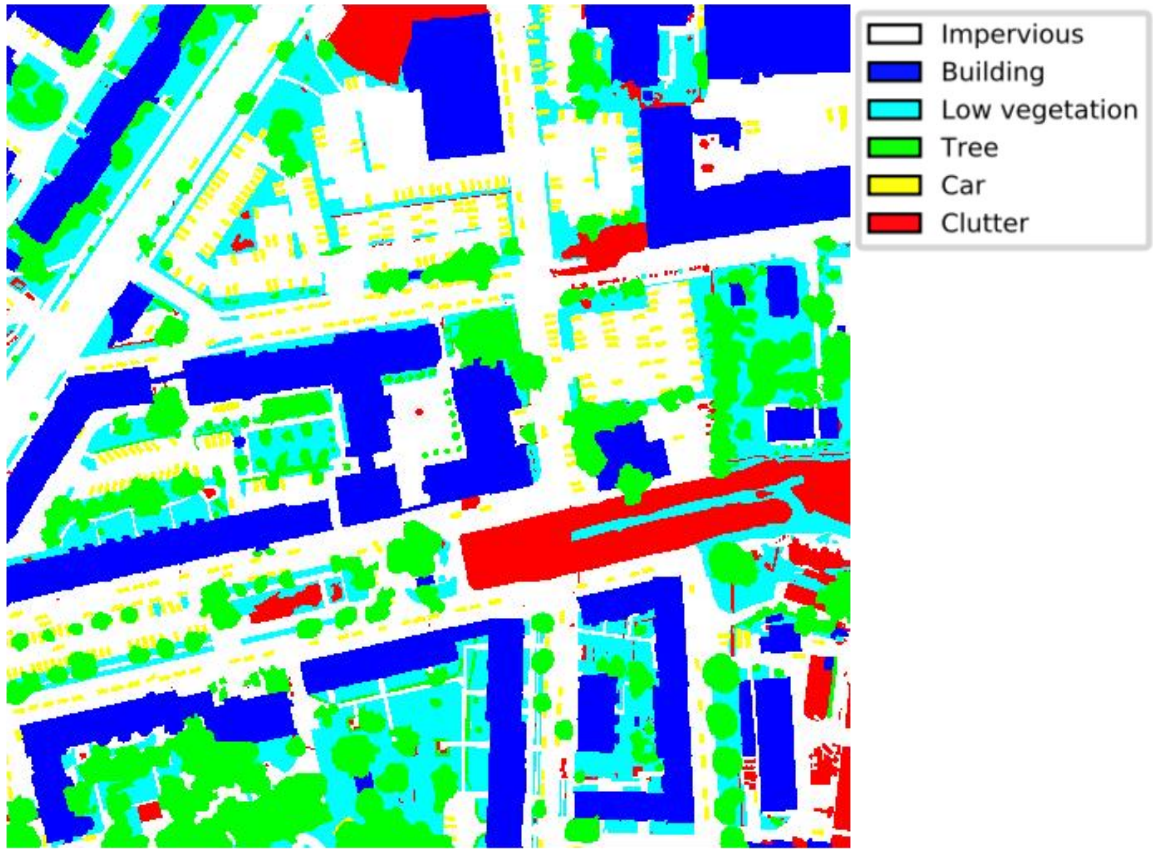
Input Pipeline challenges: avoid CPU-GPU bottleneck

- Goal: Decoupling data preprocessing from Accelerator Training



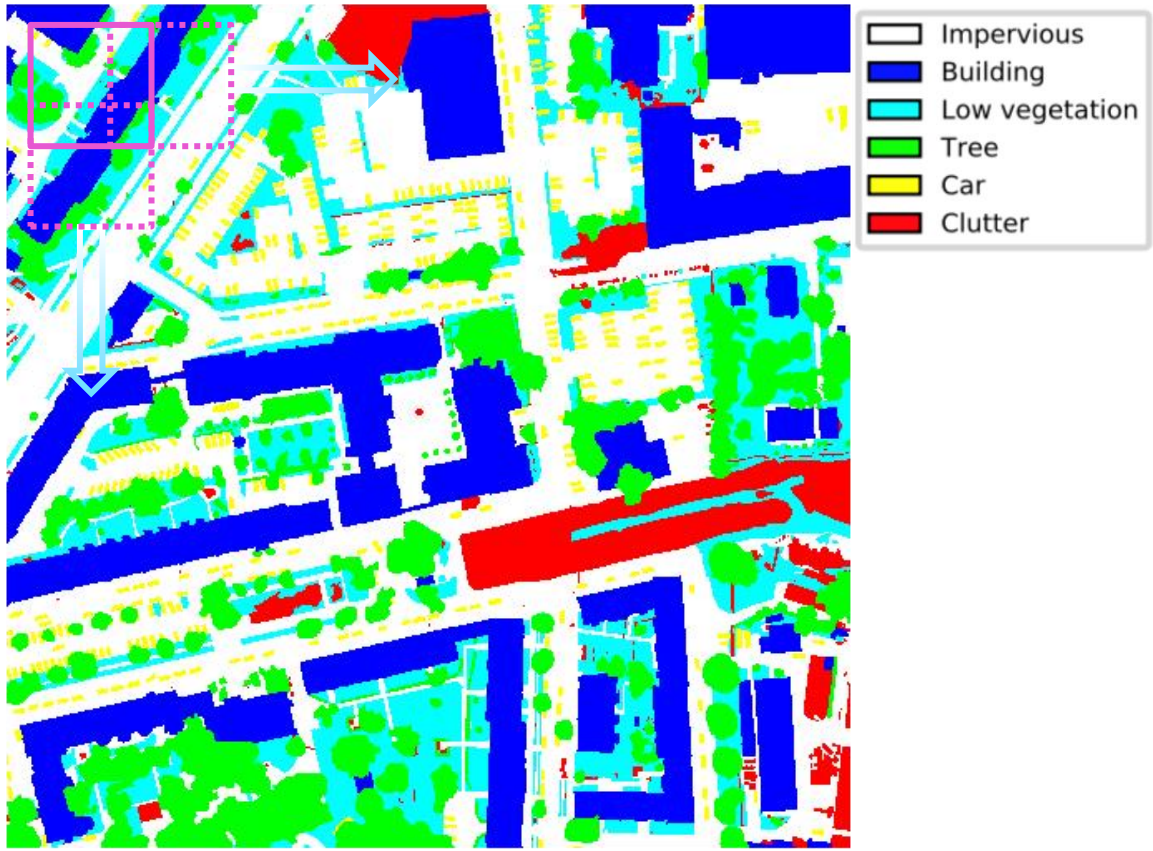
(Simplified, in reality there is always *some* idle time on both devices)

Patch Extraction



 http://www2.isprs.org/commissions/comm3/wg4/2d-sem-label-potsdam.html

Patch Extraction



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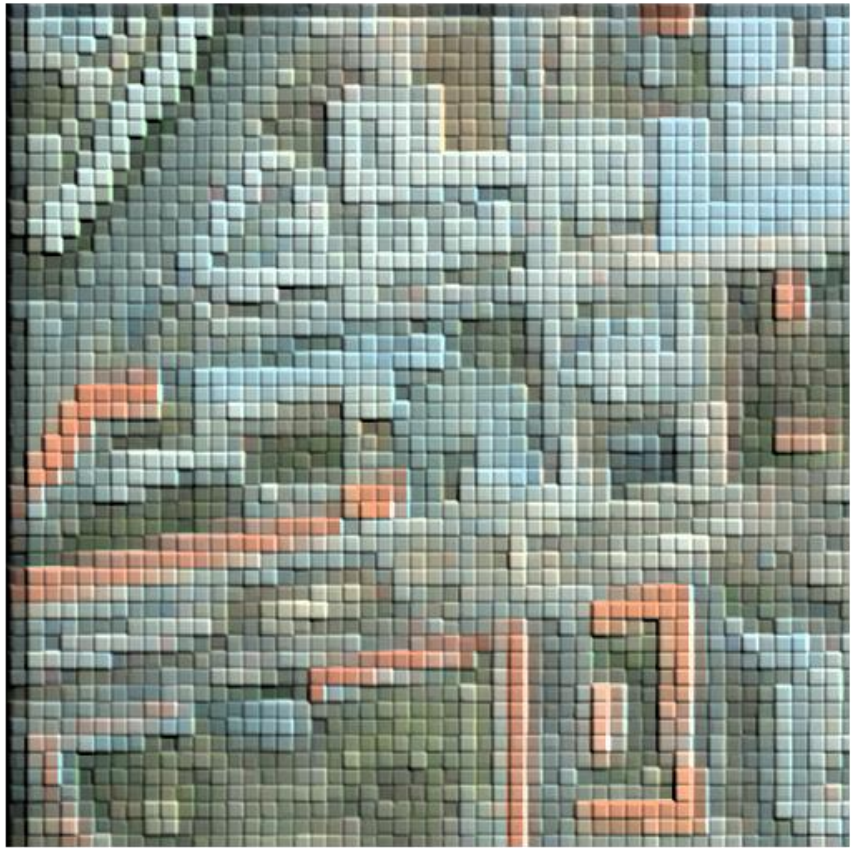
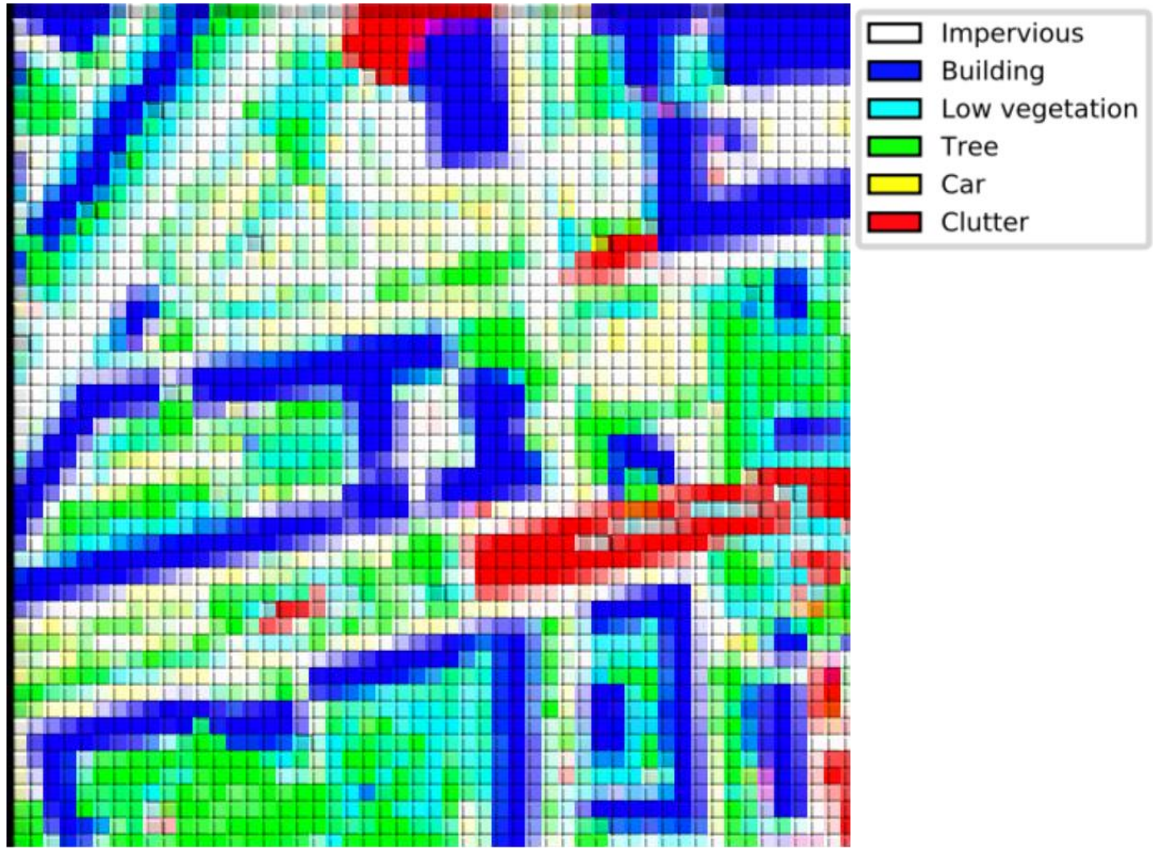
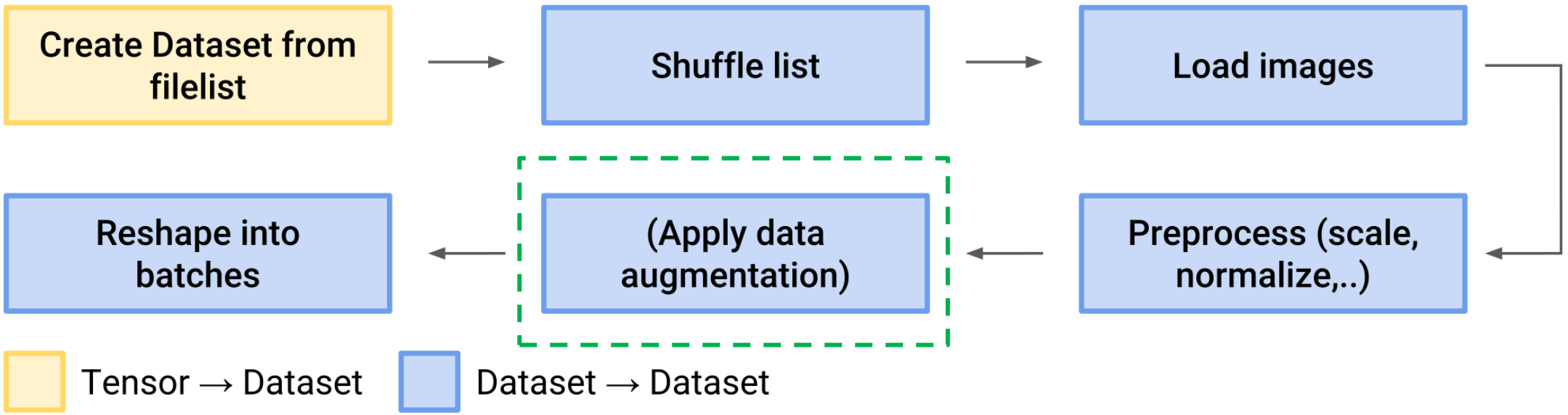
Supervised Semantic Segmentation Task Examples: ISPRS dataset (Potsdam)





 http://www2.isprs.org/commissions/comm3/wg4/2d-sem-label-potsdam.html

- Practical advantage: Easy ETL (Extract-Load-Transform) chaining for complex data augmentation



Input Pipeline: Data Augmentation

- More data helps Model Performances
- Data Augmentation is a way to artificially produce more Annotated data at low cost to train the Model
- Apply same spatial transformation to both aerial and mask patch pair, color transformation only to aerial patch

Input Pipeline: implementation details

```
with tf.device('/CPU:0'):
    def get_dataset(img_dir, mask_dir, batch_size, shuffle=True, repeat=False, augment=True, scaled=True, cachefile=None):
        images_path  = Path(img_dir)
        masks_path   = Path(mask_dir)
        images_files = sorted([str(x) for x in images_path.iterdir() if x.is_file() and x.suffix == '.tif'])
        masks_files  = sorted([str(x) for x in masks_path.iterdir()  if x.is_file() and x.suffix == '.tif'])

        # checking the equality of the two list lenghts
        assert len(images_files) == len(masks_files), " (Error) The Aerial image count does not match Mask counts!"
        len_images = len(images_files)

        if cachefile:
            cache_file_name = '/tmp/' + cachefile
          else:
            cache_file_name = ''

        # images file names dataset
        images_ds = tf.data.Dataset.from_tensor_slices(images_files)
        masks_ds = tf.data.Dataset.from_tensor_slices(masks_files)
        .
        .
        .
```

Input Pipeline: implementation details

```
with tf.device('/CPU:0'):
    def get_dataset(img_dir, mask_dir, batch_size, shuffle=True, repeat=False, augment=True, scaled=True, cachefile=None):
        .
        .
        .

        # zipping the aerial and mask dataset
        patch_pair_ds = tf.data.Dataset.zip((images_ds, masks_ds))
        if shuffle:
            patch_pair_ds = patch_pair_ds.shuffle(len_images)
        patch_pair_ds = patch_pair_ds.map(tf_get_image, num_parallel_calls= AUTOTUNE).prefetch(AUTOTUNE)

        # start making patches
        if scaled:
            patch_pair_ds = patch_pair_ds.map(make_patches_scaled, num_parallel_calls= AUTOTUNE)
        else:
            patch_pair_ds = patch_pair_ds.map(make_patches, num_parallel_calls= AUTOTUNE)
        patch_pair_ds = patch_pair_ds.apply(tf.data.Dataset.unbatch).cache(filename=cache_file_name)
        if augment:
            patch_pair_ds = patch_pair_ds.map(make_augmentation, num_parallel_calls= AUTOTUNE).prefetch(AUTOTUNE)
        else:
            patch_pair_ds = patch_pair_ds.map(no_augmentation, num_parallel_calls= AUTOTUNE).prefetch(AUTOTUNE)
        # repeat is not necessary as keras fit method will use epochs parameter for repetition
        if repeat:
            patch_pair_ds = patch_pair_ds.repeat()
        if shuffle:
            patch_pair_ds = patch_pair_ds.shuffle(600)
        patch_pair_ds = patch_pair_ds.batch(batch_size)
        patch_pair_ds = patch_pair_ds.prefetch(AUTOTUNE)
        return patch_pair_ds
```

Input Pipeline Performance

Without Caching:

```
[24]: timepipeline(train_ds, batch_size=BATCH_SIZE)

100% 1000/1000 [03:40<00:00, 4.53it/s]

batche size: 50
1000 batches: 220.8209400177002 s
4.52856 Batches/s
226.42780 Images/s
```

With Disk Caching:

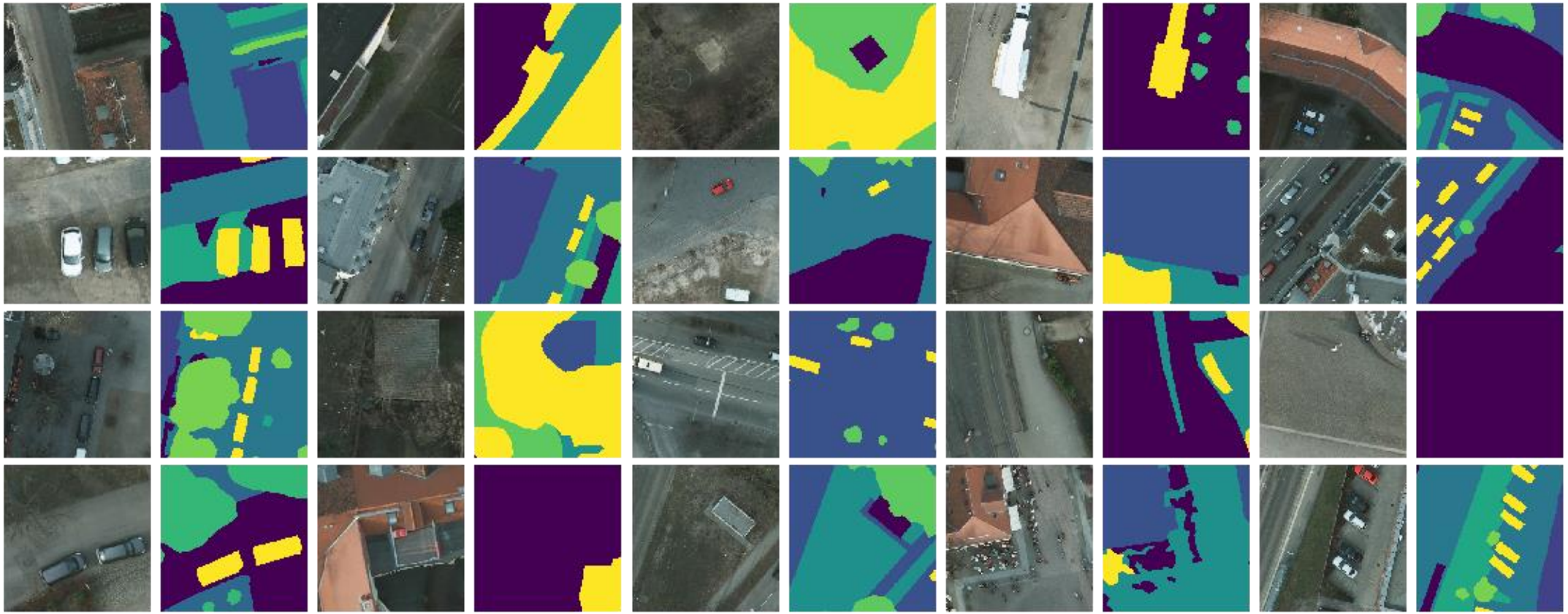
```
[35]: timepipeline(train_ds, batch_size=BATCH_SIZE)

100% 1000/1000 [01:14<00:00, 13.48it/s]

batche size: 50
1000 batches: 74.26196789741516 s
13.46584 Batches/s
673.29215 Images/s
```

With Memory Caching:

```
[38]: timepipeline(train_ds, batch_size=BATCH_SIZE)

100% 1000/1000 [01:13<00:00, 13.56it/s]

batche size: 50
1000 batches: 73.79464364051819 s
13.55112 Batches/s
677.55595 Images/s
```

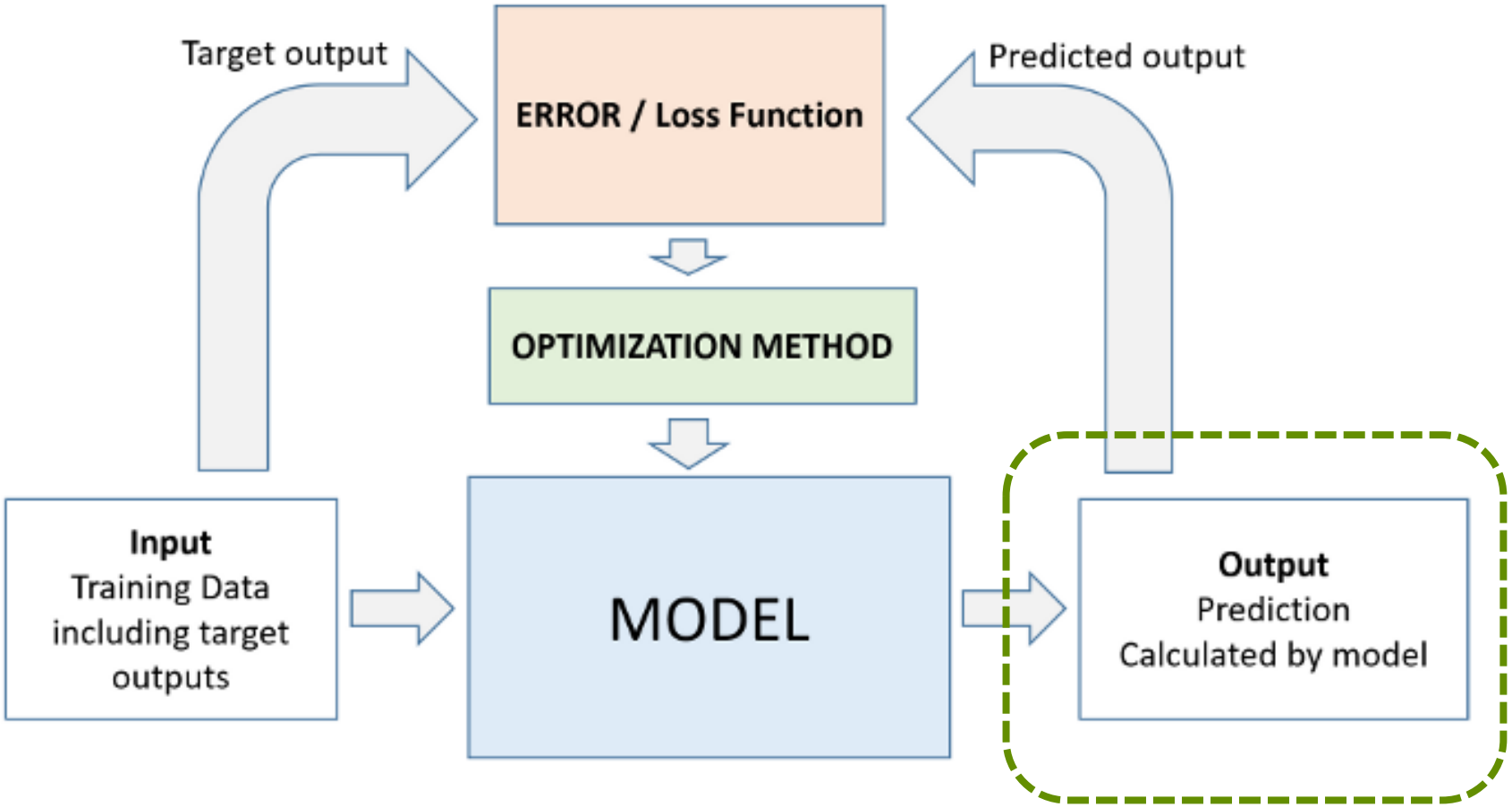
Input Pipeline Patch Pairs Example

```
[47]: train_ds = get_dataset(img_dir=train_img_dir, mask_dir=train_mask_dir, batch_size=BATCH_SIZE, shuffle=True, repeat=True, augment=True, scaled=False, cachefile=None)

[ ]: val_ds = get_dataset(img_dir=val_img_dir, mask_dir=val_mask_dir, batch_size=BATCH_SIZE, shuffle=False, repeat=True, augment=False, scaled=False, cachefile=None)
```

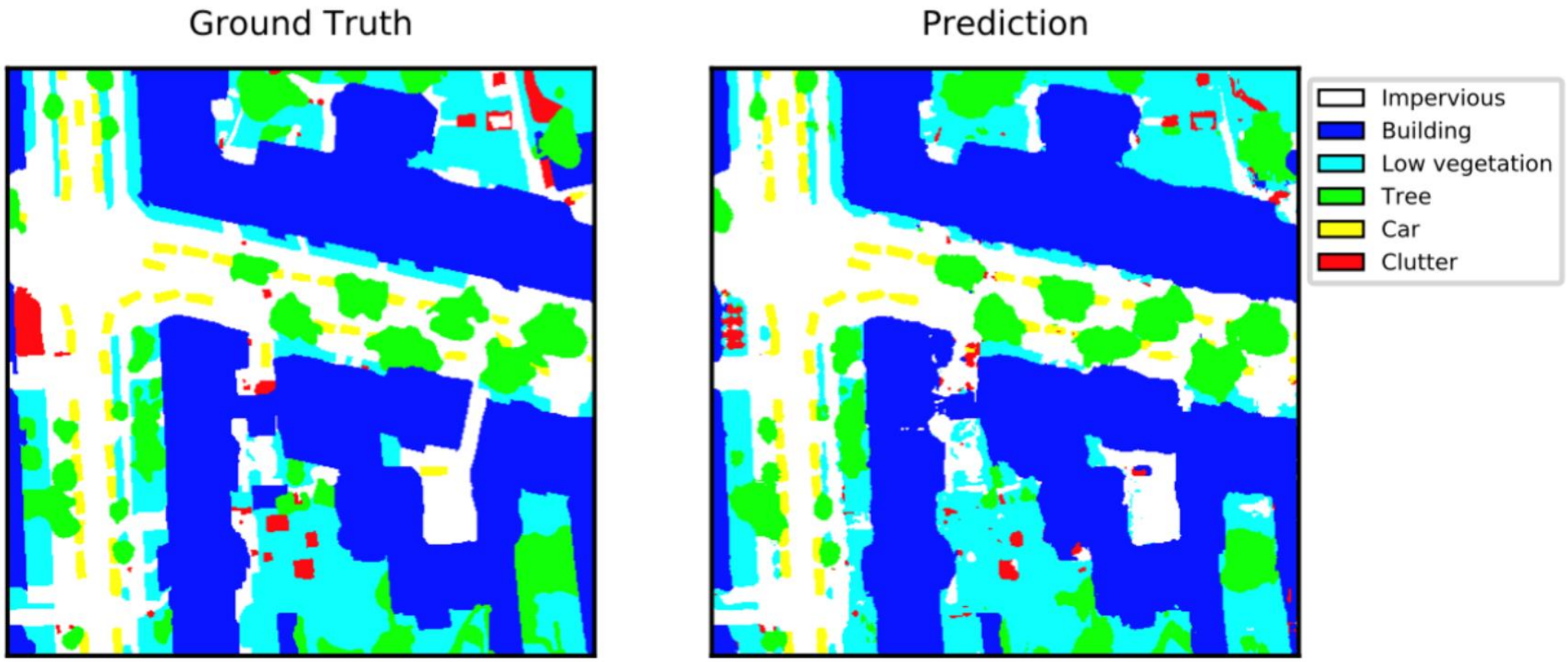


Model Performance Metrics

Performance Metrics



Natural Metric for Image Comparison: Accuracy



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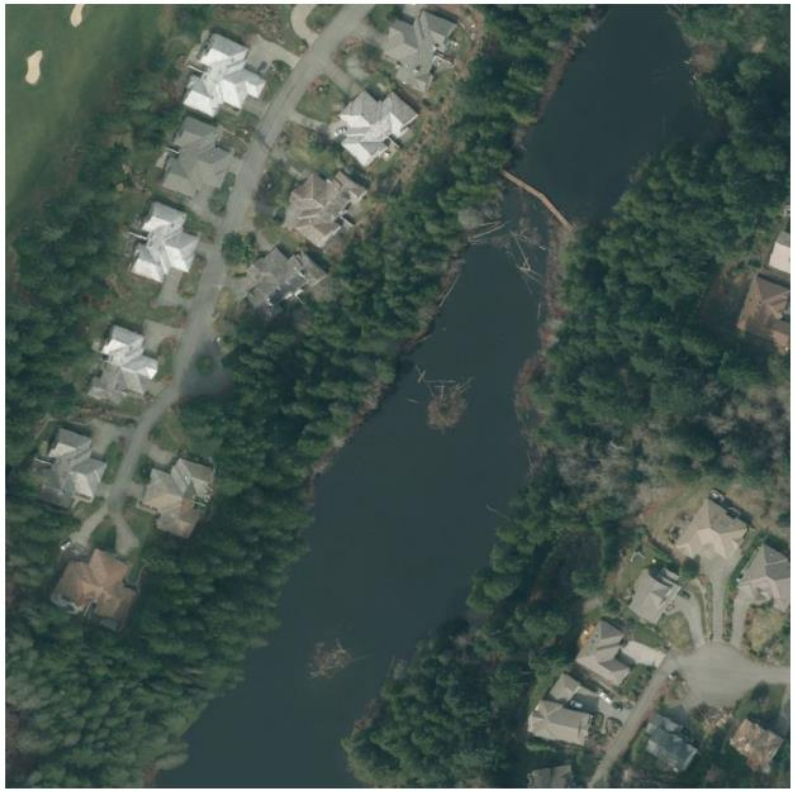
Performance Metrics: Accuracy is not enough For Segmentation



Kitsap County, WA

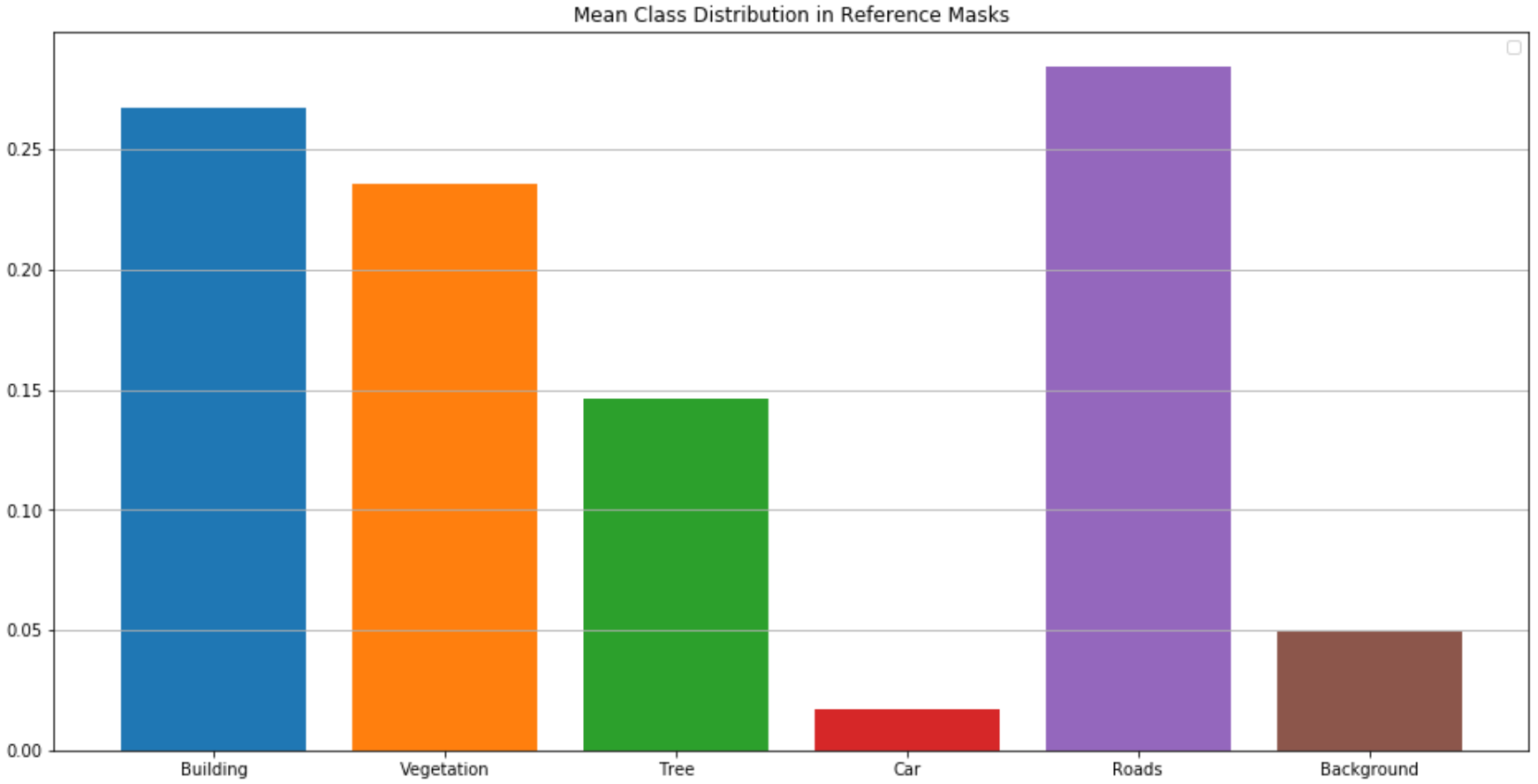
Kitsap County, WA – Reference

≈ 10% Building

Model = all Background

≈ 90% Accuracy

ISPRS Class Distribution



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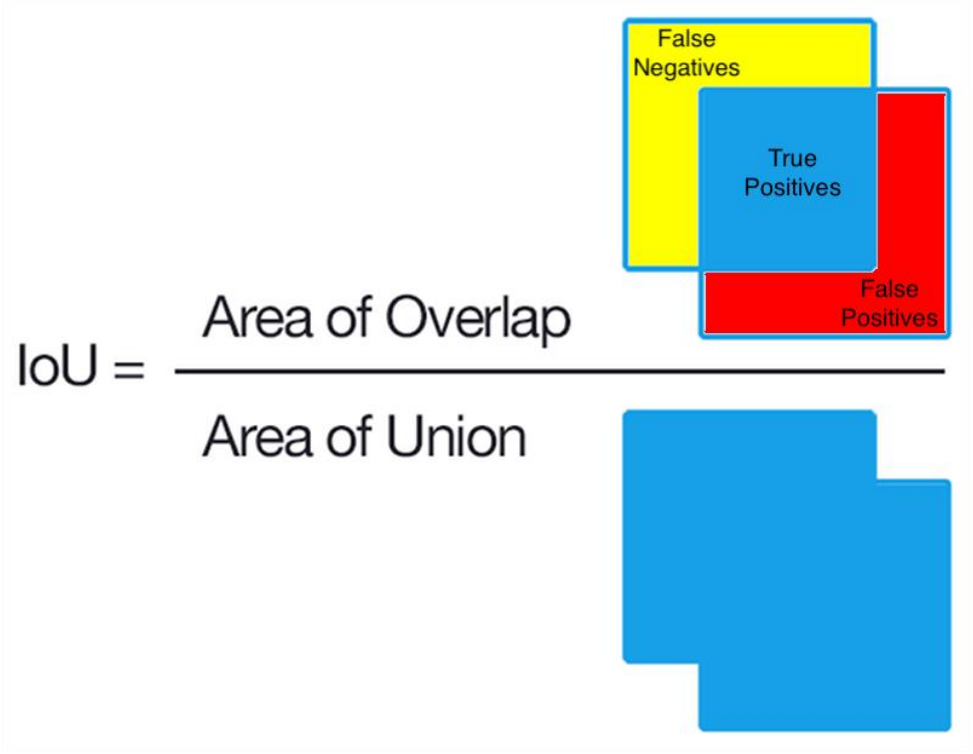
A Better Segmentation Metric: Jaccard Index (Intersection Over Union)



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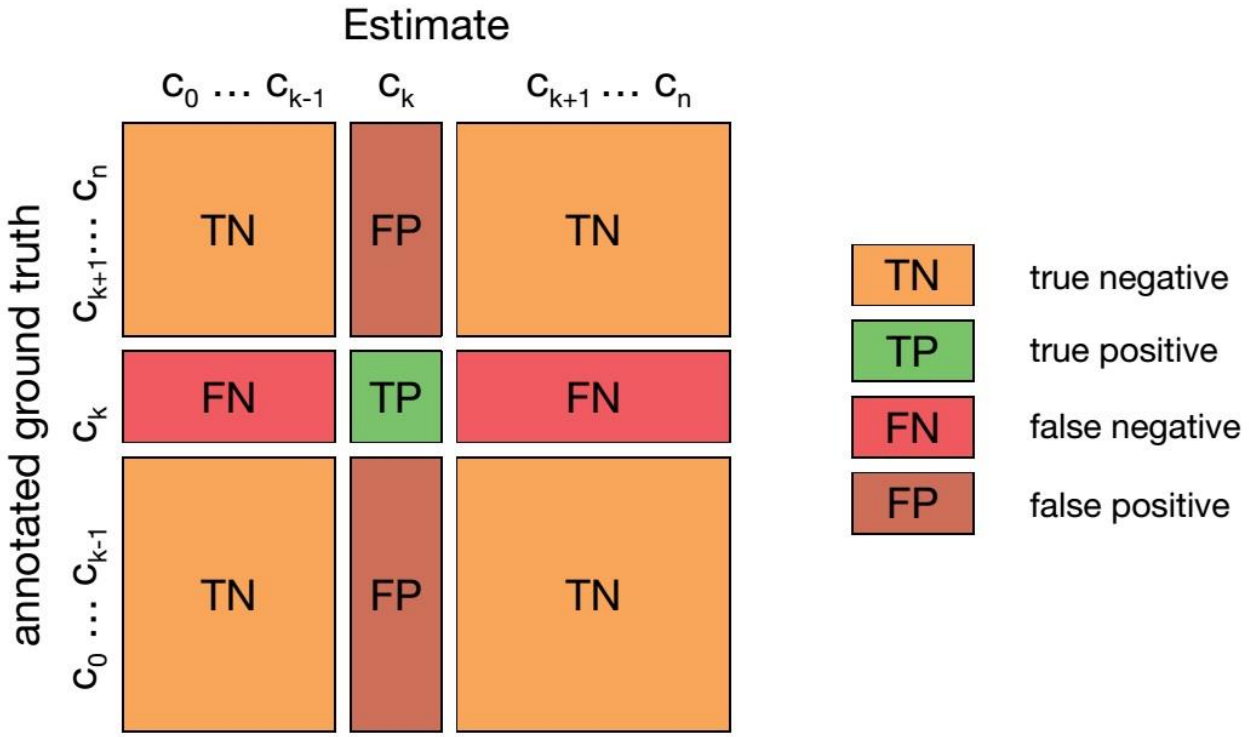
Metrics Formulas:

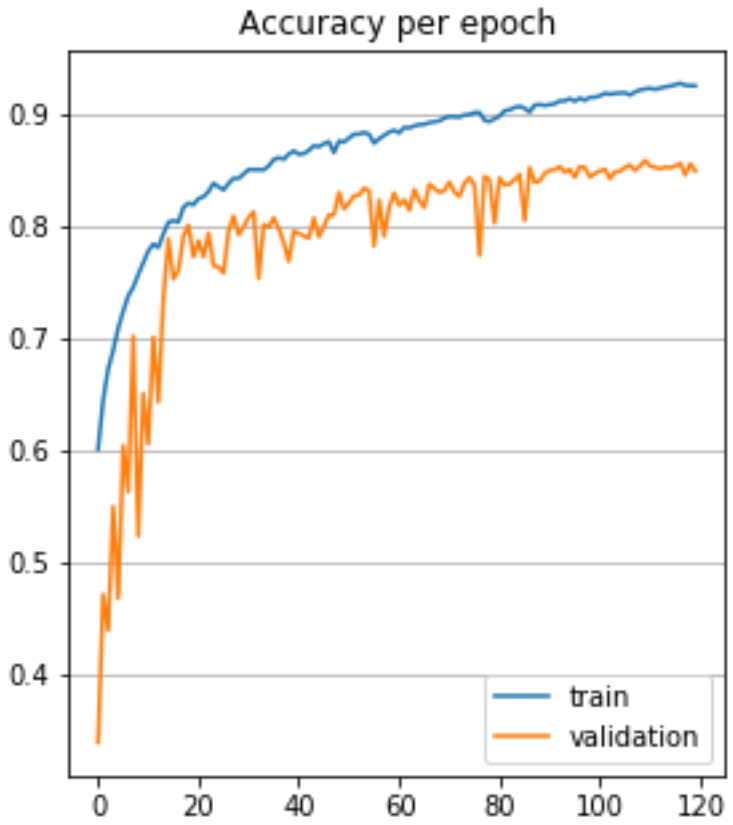
$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

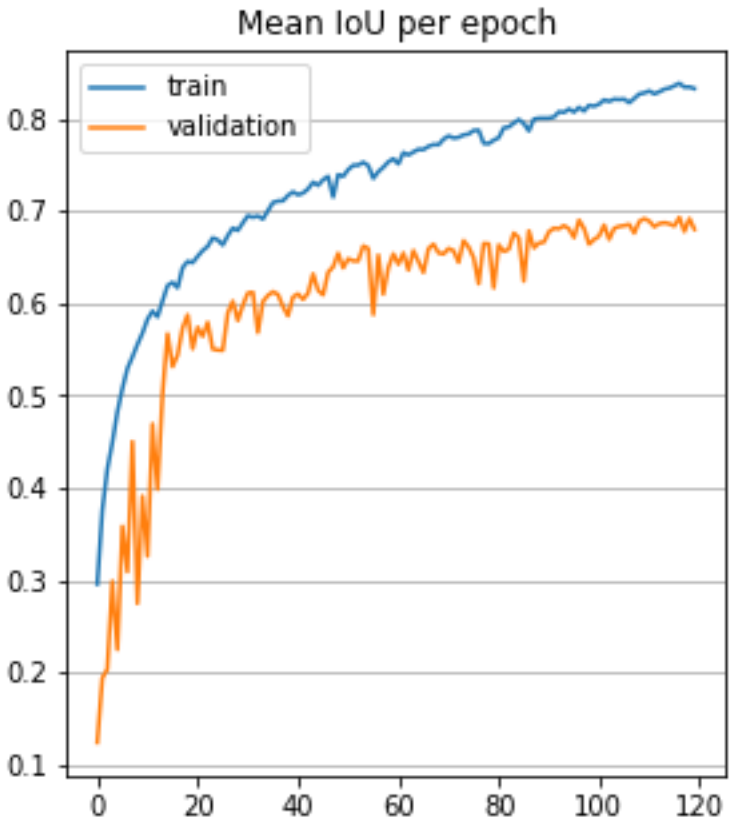
$$Jaccard\ Index\ (IoU) = \frac{TP}{TP + FP + FN}$$

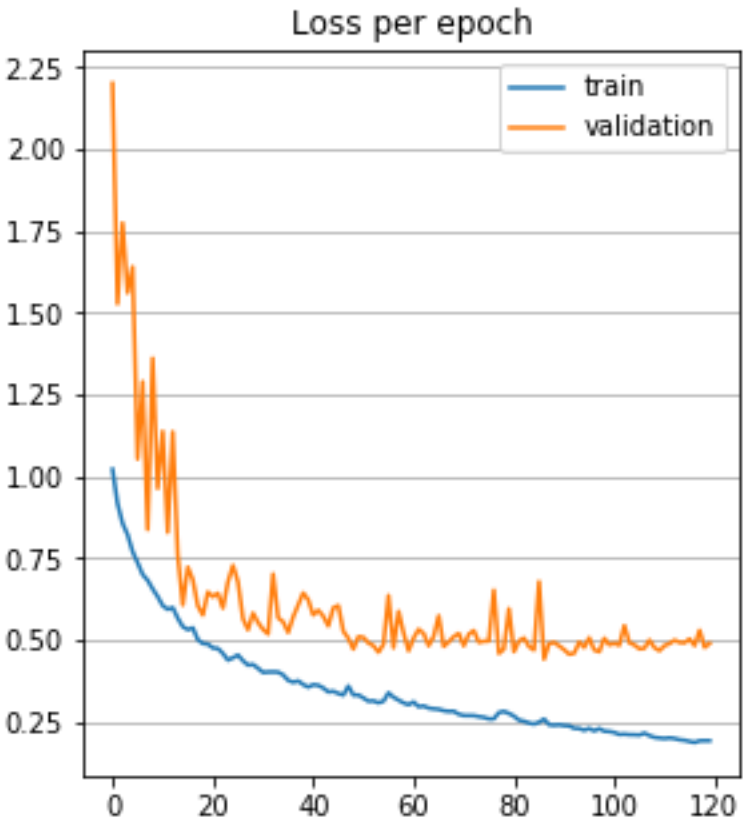


Confusion Matrix

Monitoring Metrics During Training







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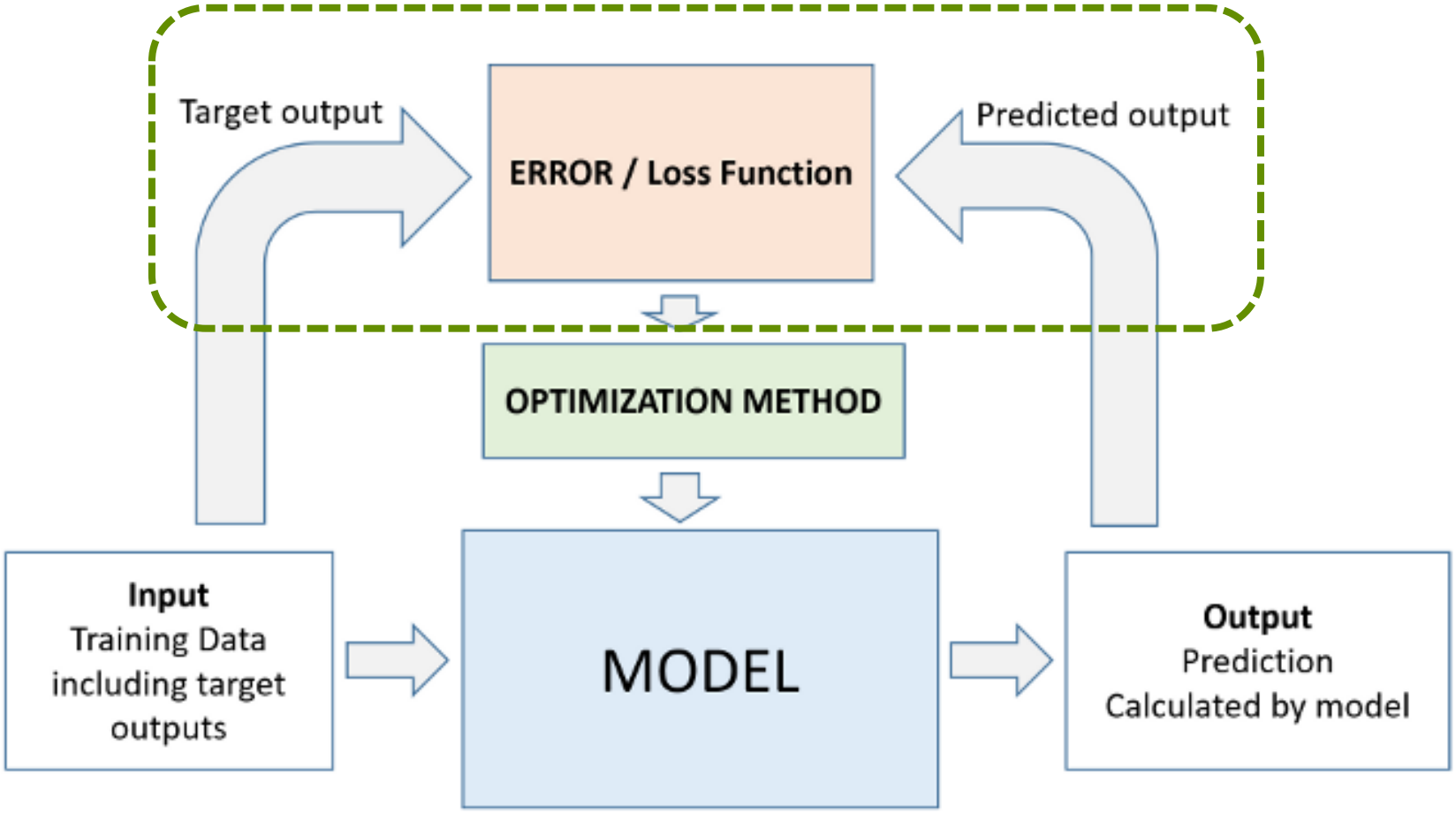
Training Callbacks

- Keras Callbacks are Predefined Functions automatically executed at the end of every epoch:
  - Checkpoint Callback: monitor a metric on validation dataset (IOU for instance) and stores the model weights only if the Performance improved
  - Reduce on Plateau Callback: reduce the learning Rate by a factor if the Performance Matric did not improve after a number of epochs
  - Early stopping callback: automatically stops training if Performance Metric did not improve after a number of epochs
  - Tensorboard callback: stores training and Validation Metrics for live Monitoring

Model Loss Function

Loss Function



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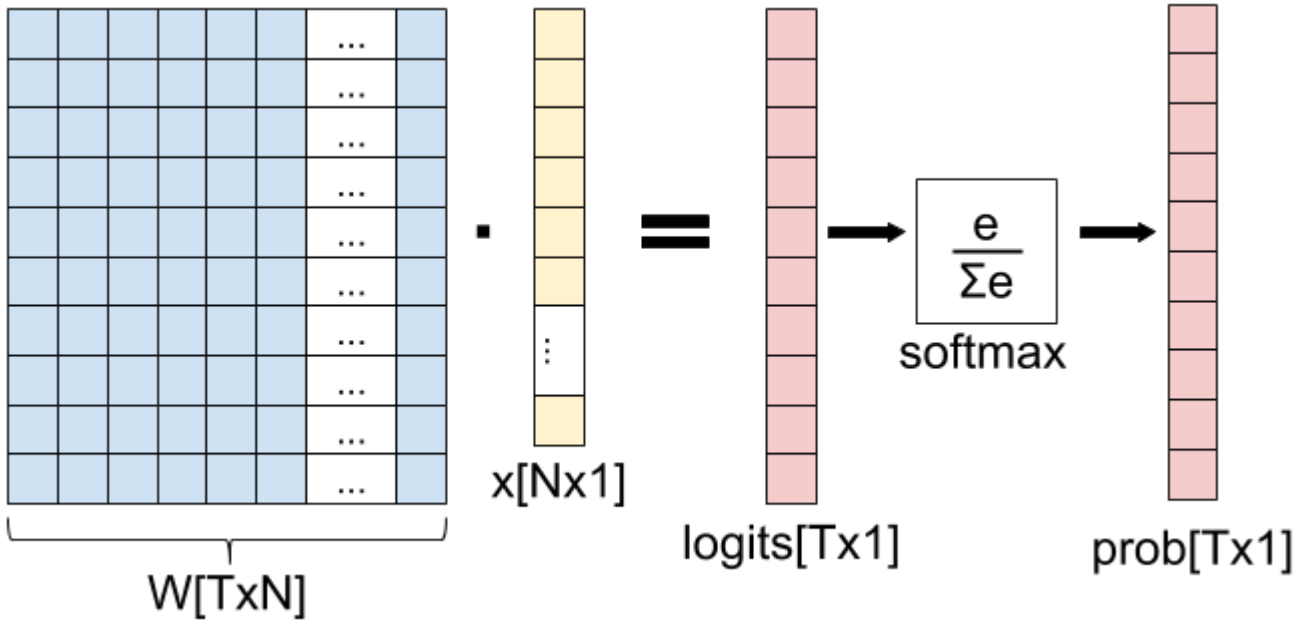
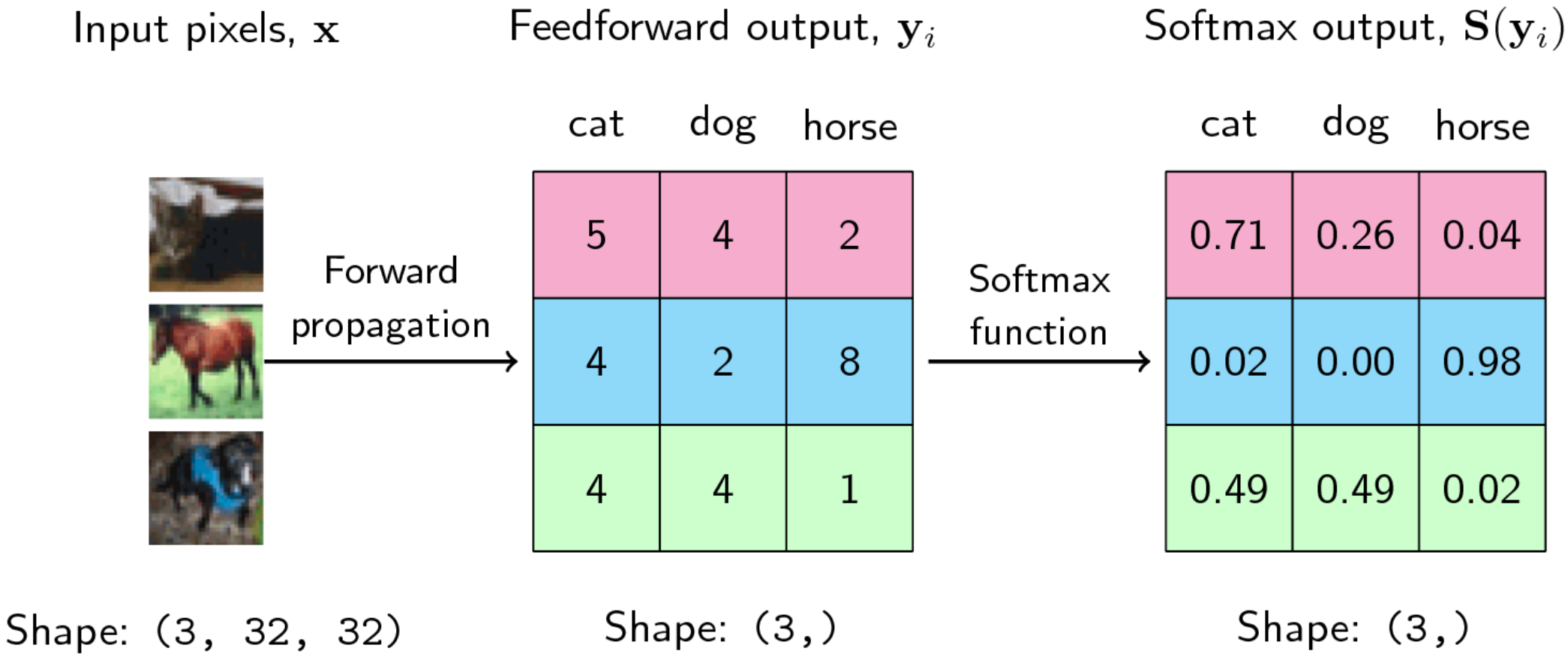
The Softmax Layer



The Softmax Layer



Used Loss Functions:

- Multiclass Cross Entropy:

$$L(\hat{y}, y) = -\sum_{k}^{K} y^{(k)} \log \hat{y}^{(k)}$$

- Focal Loss:

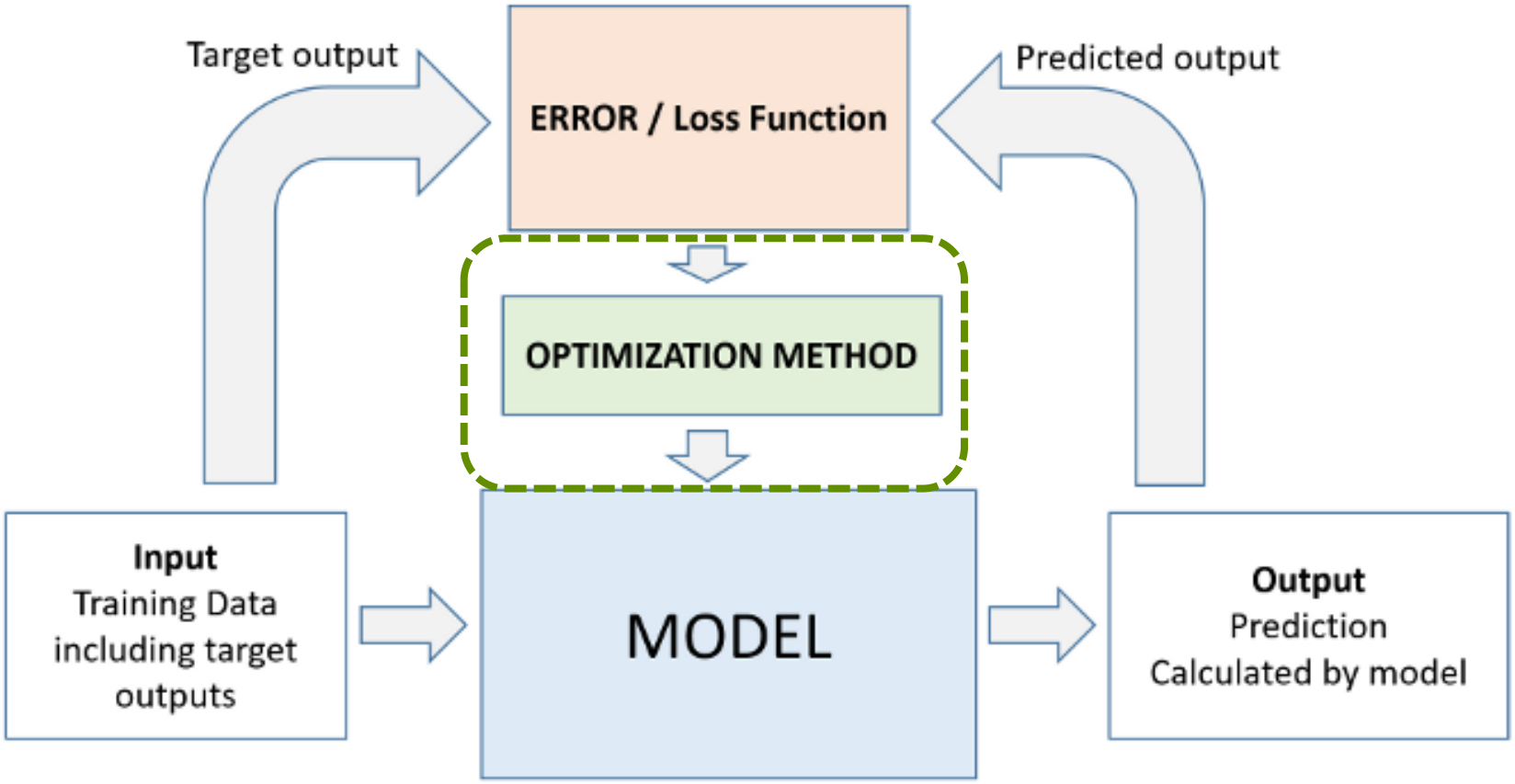
$$\mathrm{FL}(p_\mathrm{t}) = -\alpha_\mathrm{t}(1 - p_\mathrm{t})^\gamma \log(p_\mathrm{t}).$$

- Jaccard Index Loss:

$$L_{IoU} = 1 - IoU = 1 - \frac{I(X)}{U(X)}$$

Model Optimization

Model Optimization



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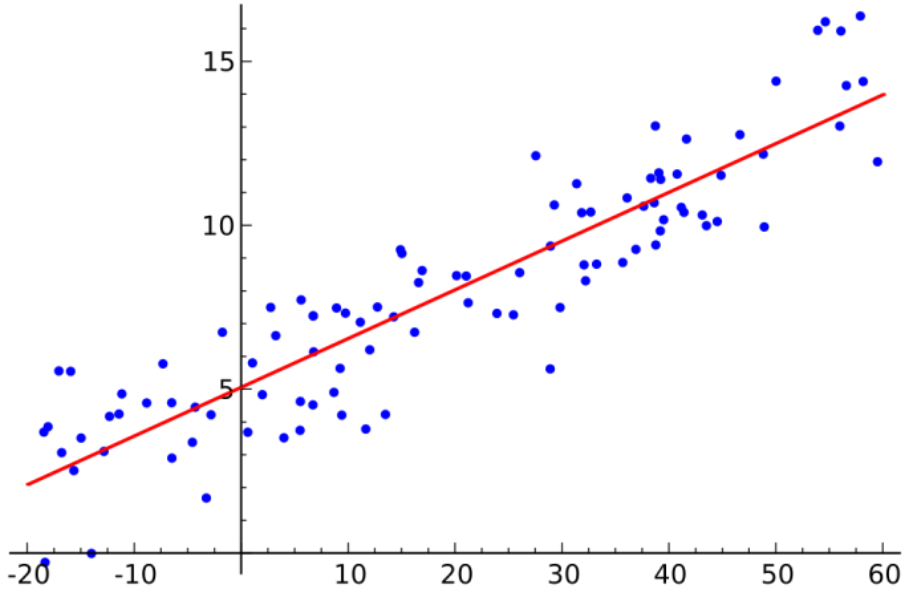
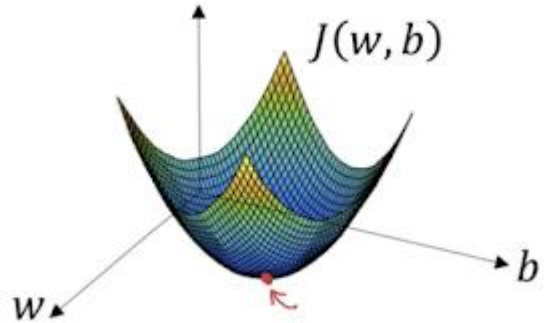
Optimization Algorithms

- The goal is to find the set of weights that minimizes the Loss function

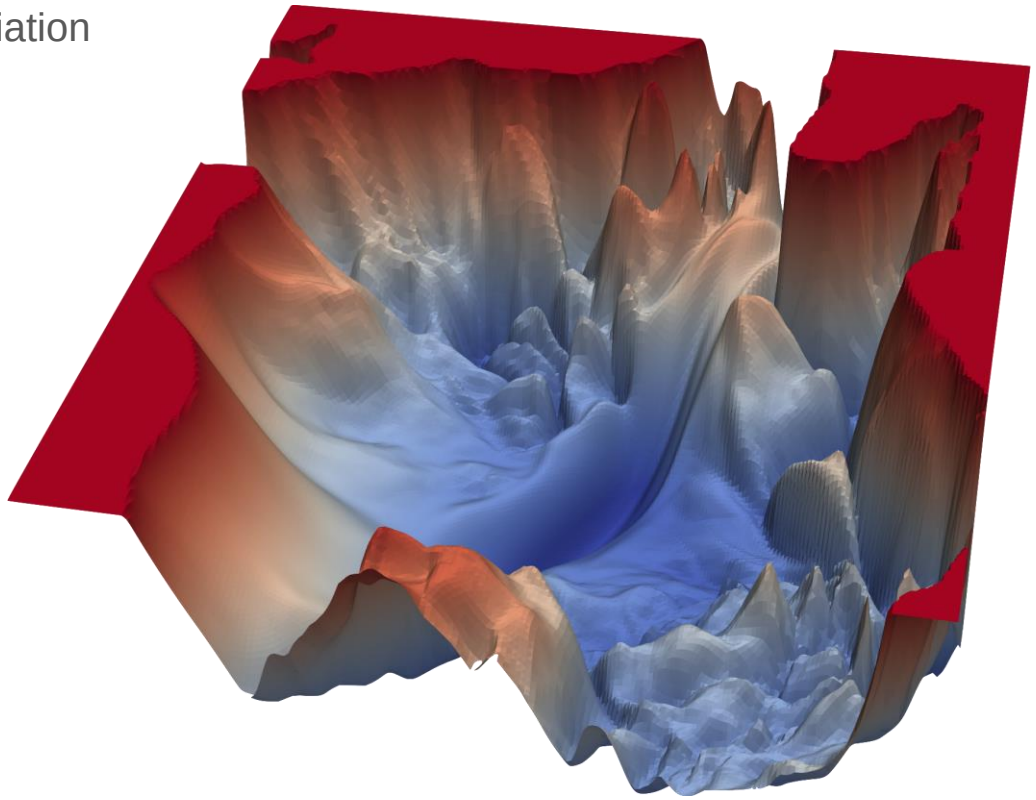
- For Linear Regression:
  - Model: $Y = w X + b$
  - Loss Function (Squared Mean Error): $J(w,b) = ||Y – w X – b||^2$





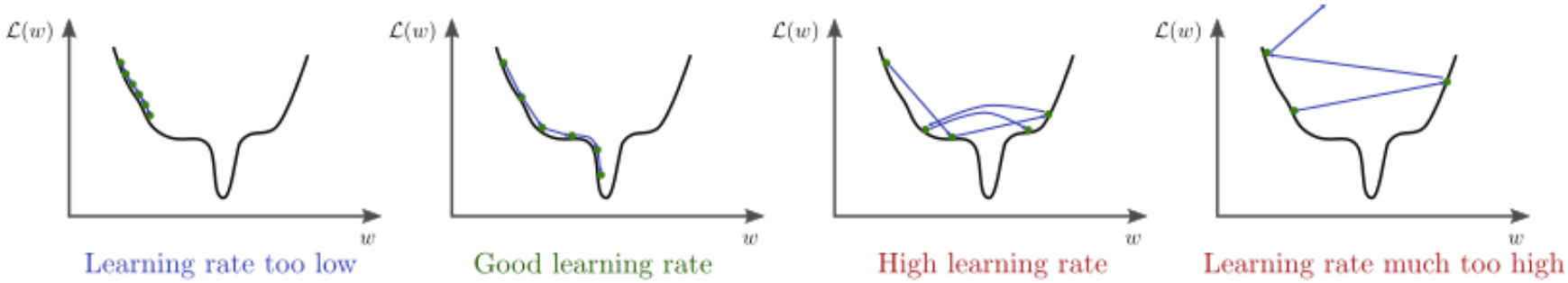
Loss Function Landscape for Neural Network

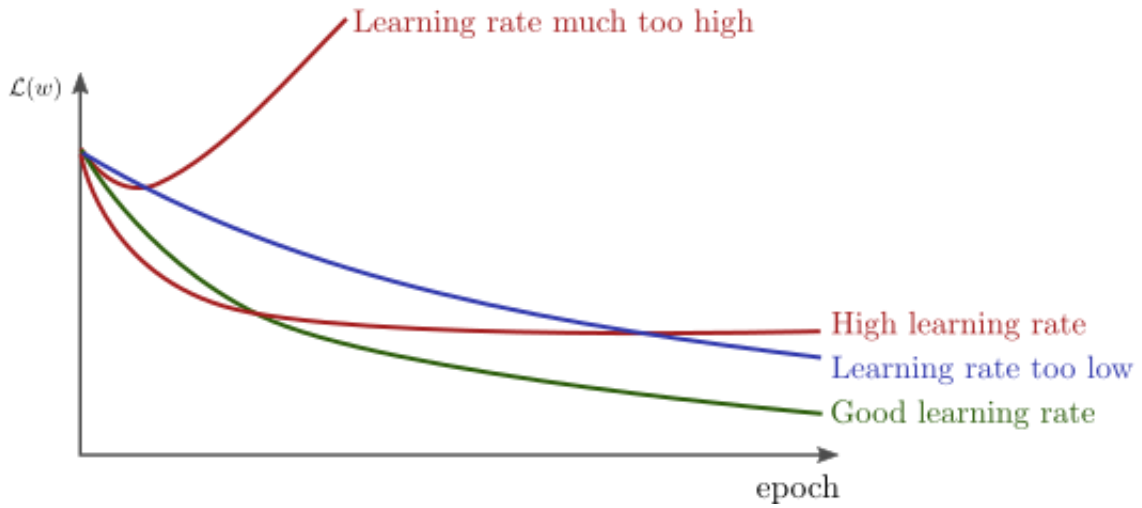
- All Optimization Algorithm are variation of Gradient Descent and are provided by Tensorflow library
- Gradient of loss function is computed using Automatic-differentiation
- Some of the best known are: SGD, RMSPROP, ADAM
  - In our work SGD with momentum is used
- The common algorithm Parameter: Learning Rate



 https://www.cs.umd.edu/~tomg/projects/landscapes/

Finding a Good Learning Rate is critical

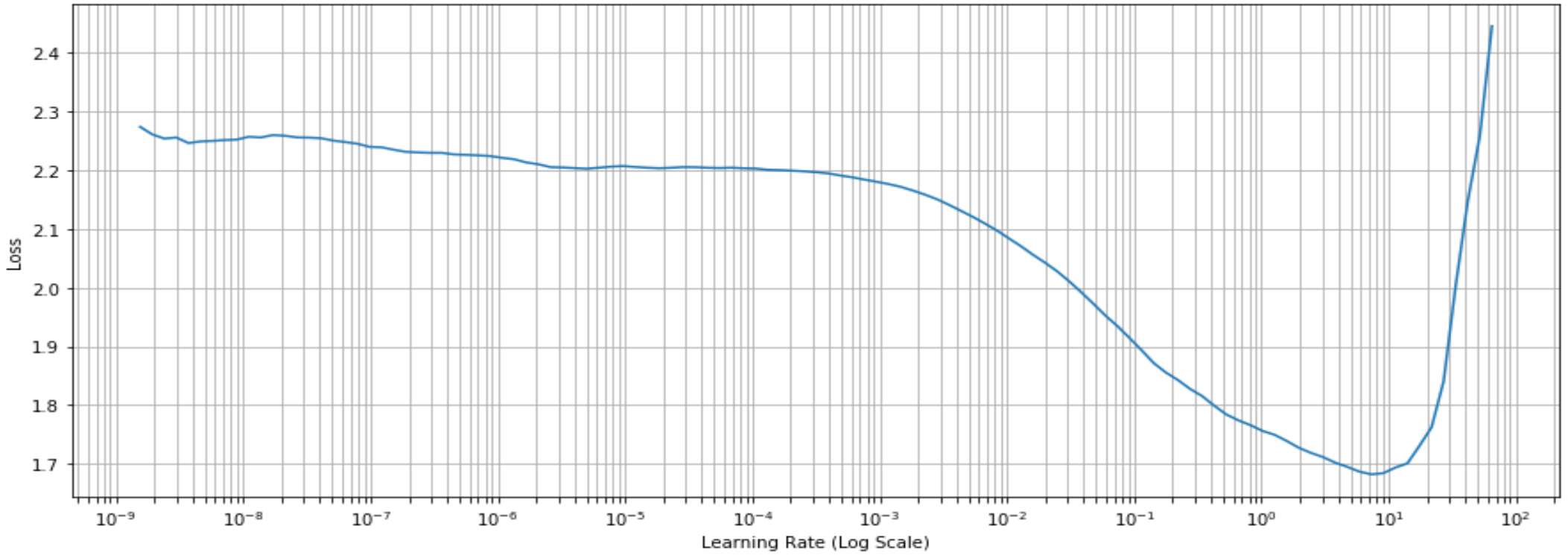




 http://www.bdhammel.com/learning-rates/

Learning Rate Finder

```
[ ]: lrf = LearningRateFinder(model)
     lrf.find(train_ds, 1e-9, 1e+2, epochs=1, stepsPerEpoch=TRAIN_STEPS_PER_EPOCH)
     lrf.plot_loss()
```



 Paper: https://arxiv.org/abs/1506.01186

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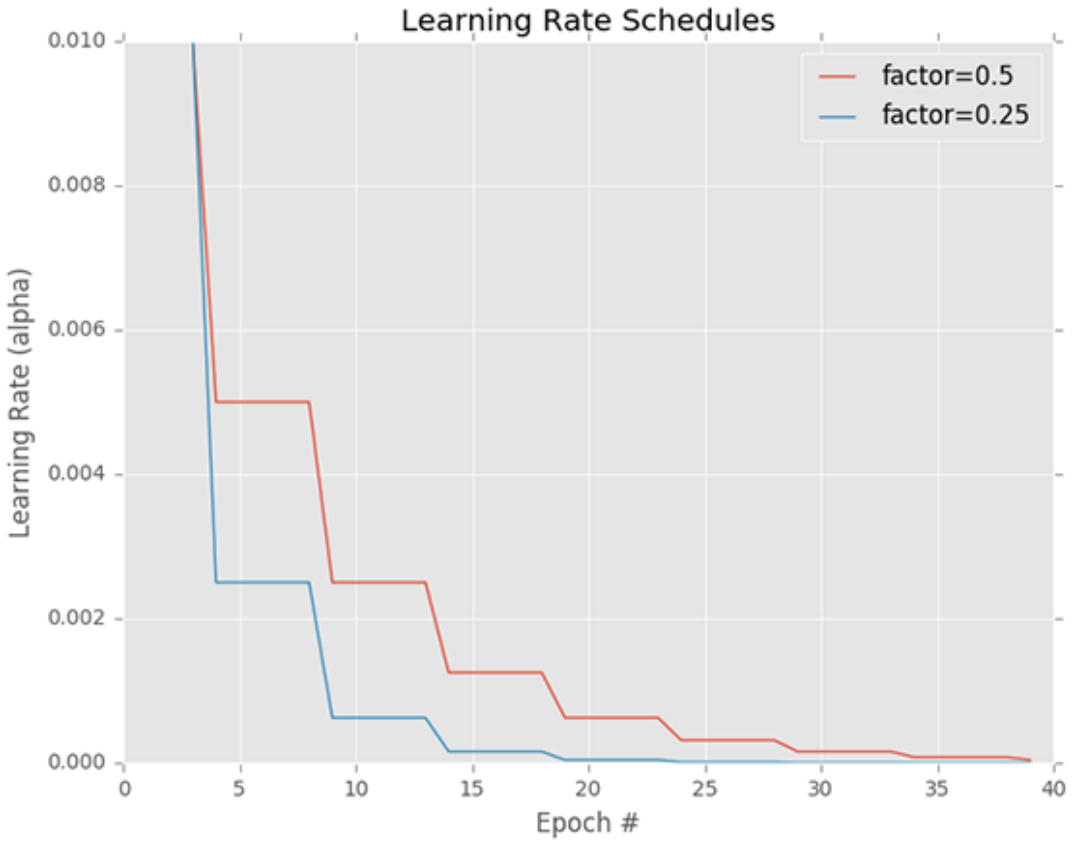
Training Strategy: Reduce on Plateau (Keras Callback)



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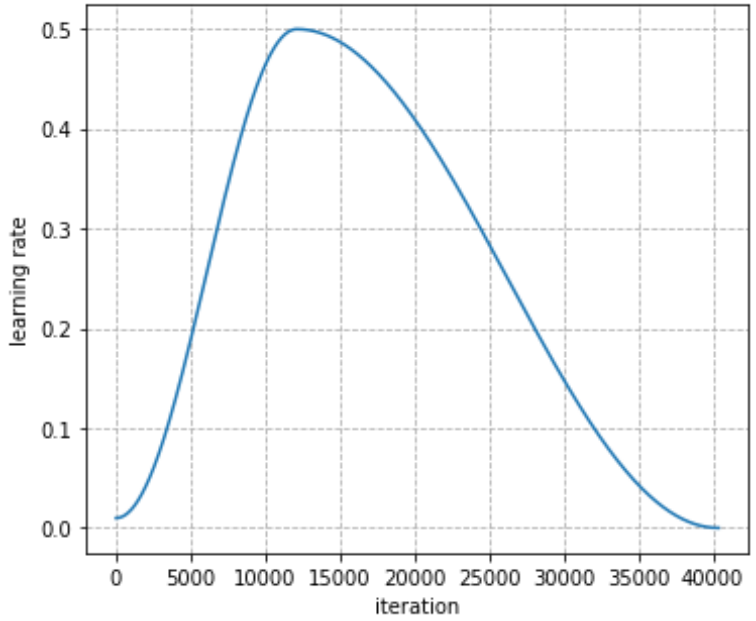
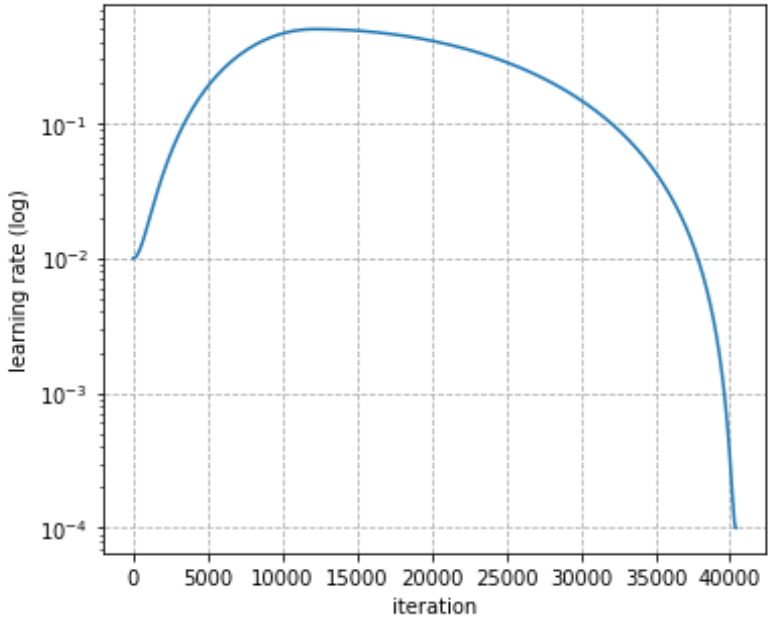
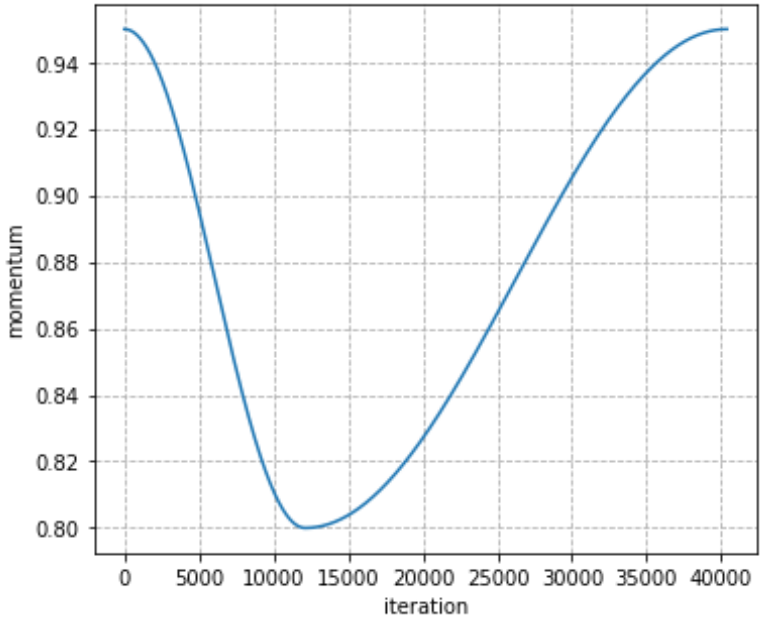
Training strategy: One Cycle Policy (Keras Callback)







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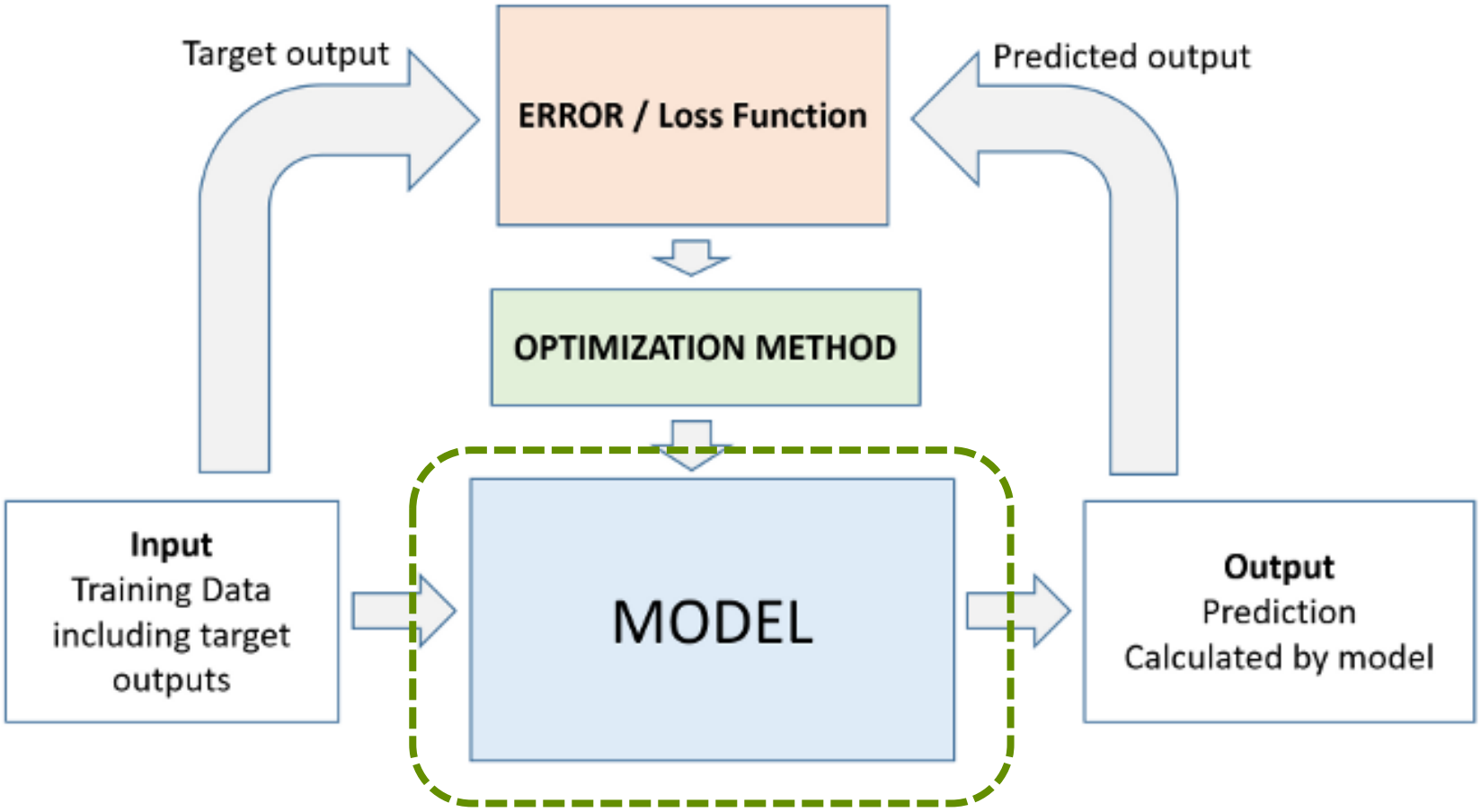
Model Architecture

Model Architecture



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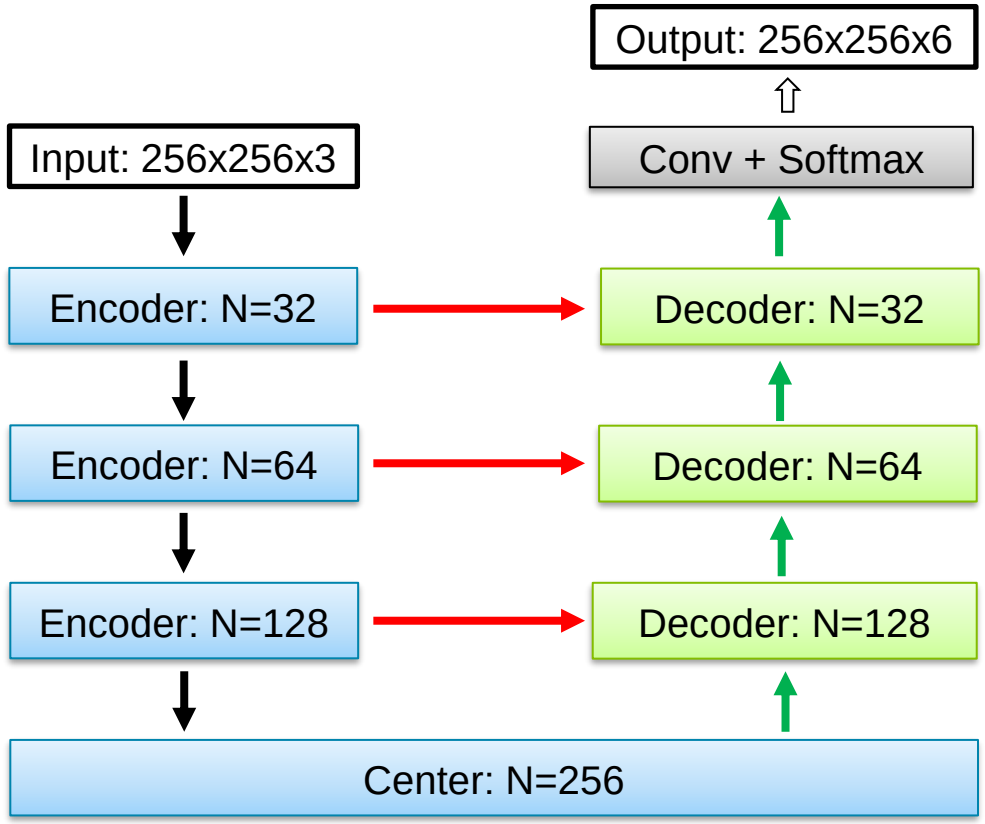
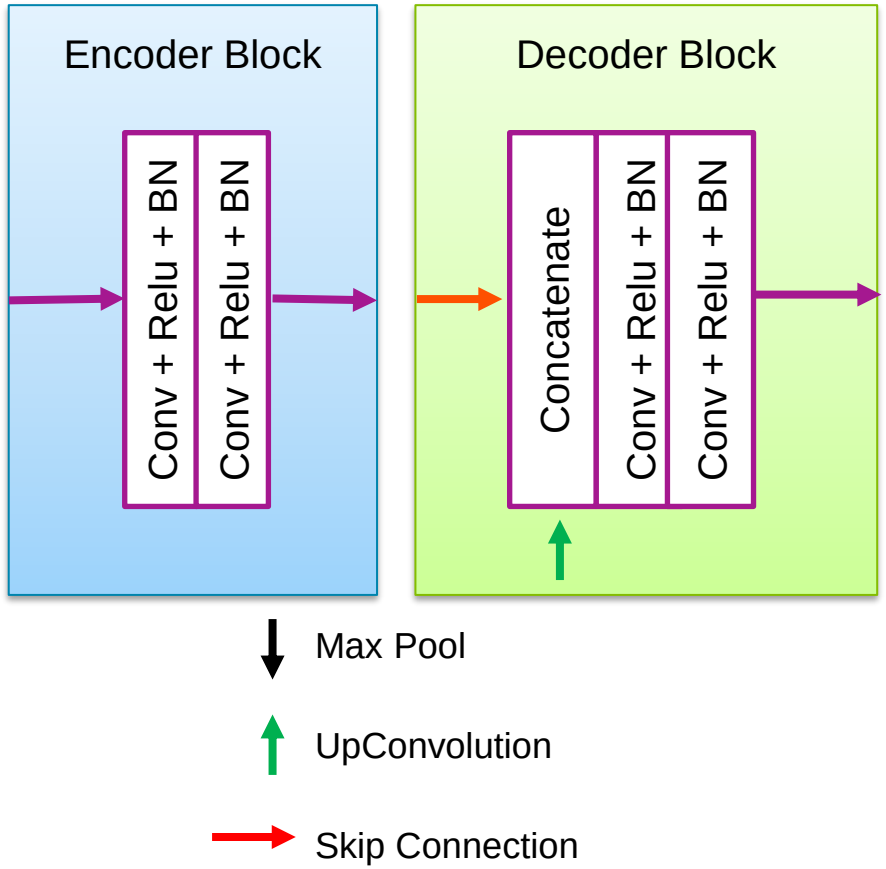
Unet: 3 Skips





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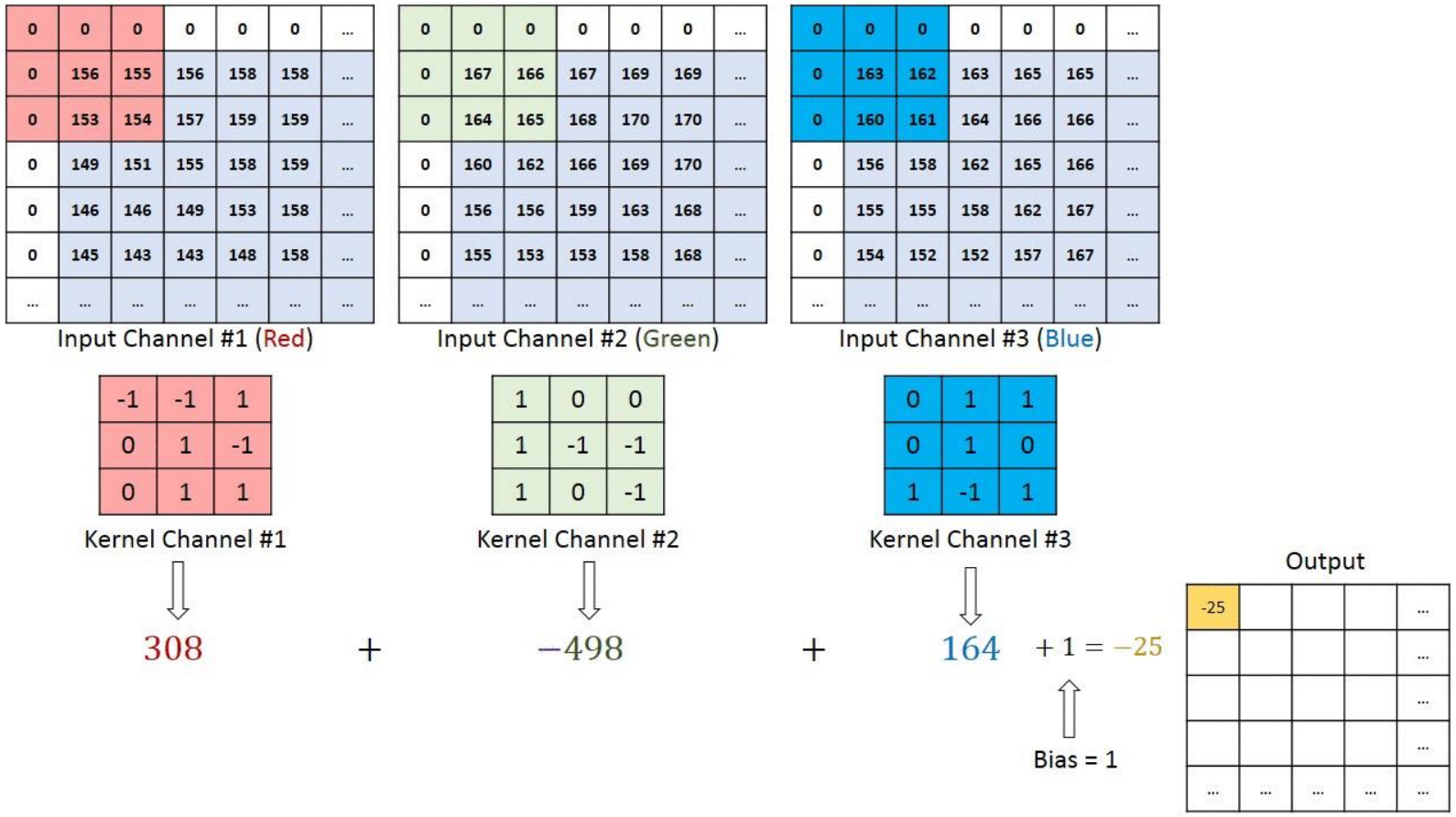
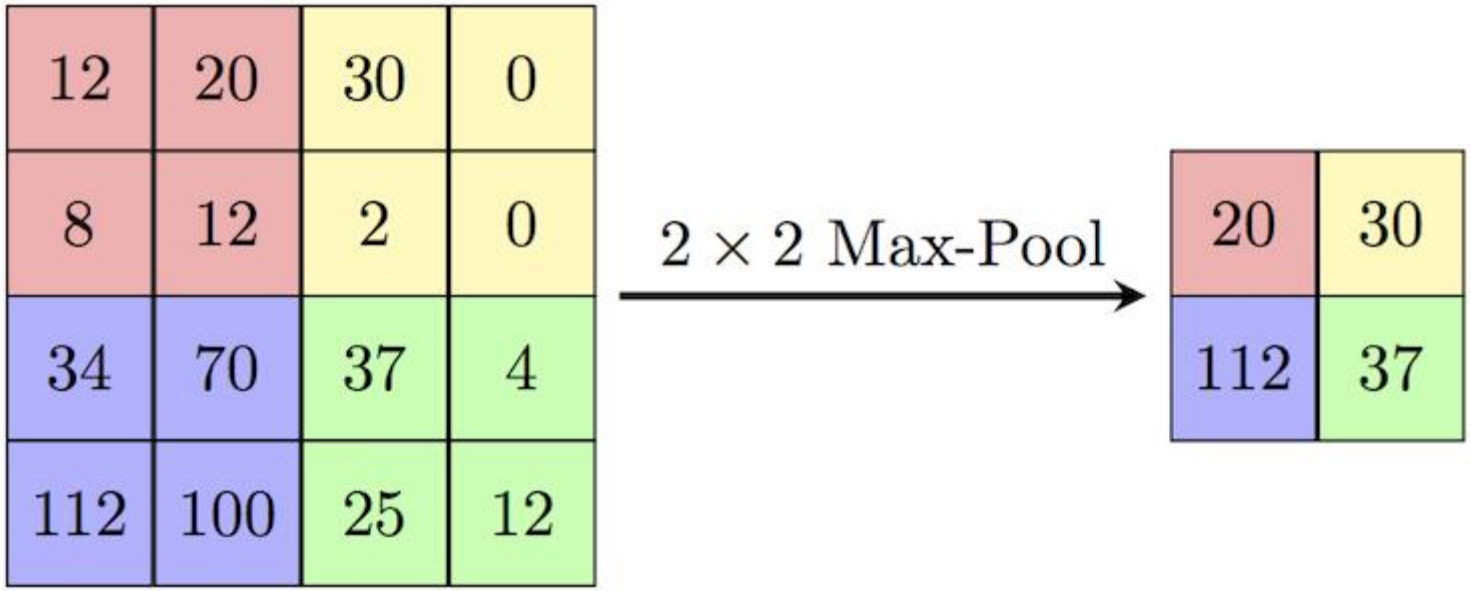
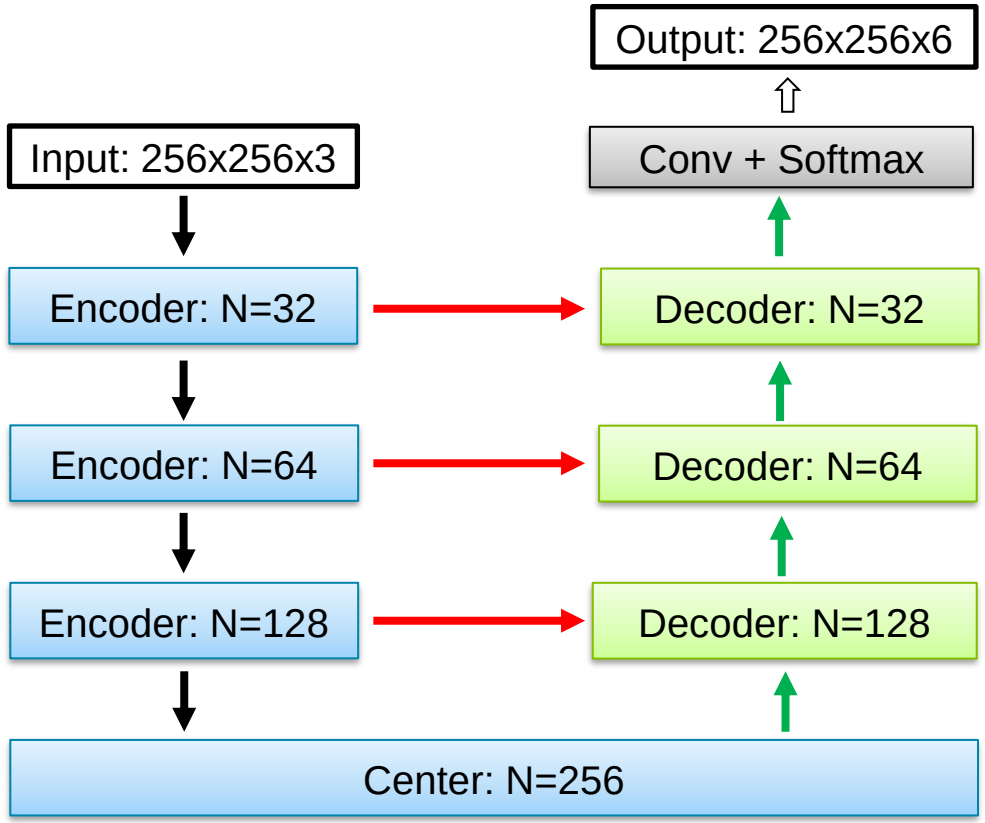
Convolution Layer in Neural Networks

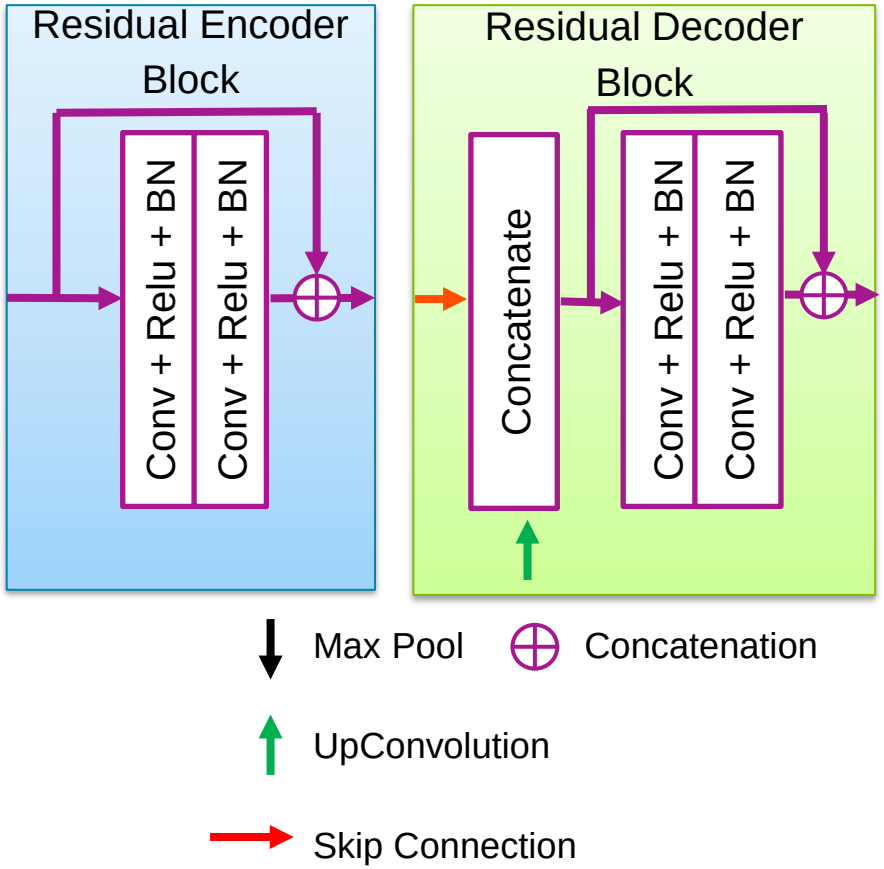


Max Pooling Layer in Neural Networks



Unet: 3 Skips + Residual Blocks (like ResNet)





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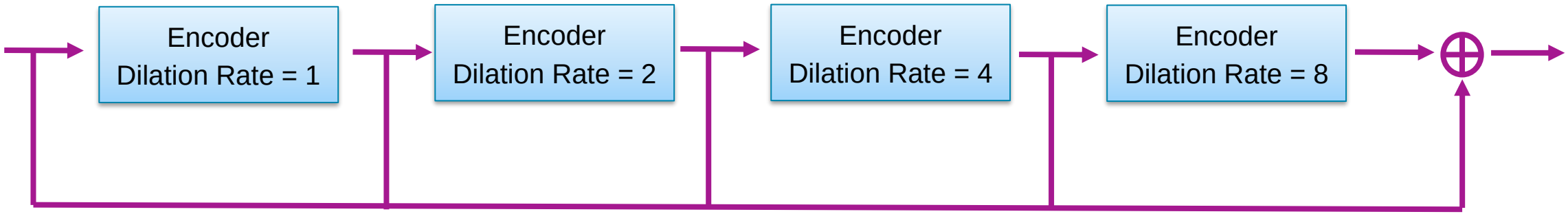
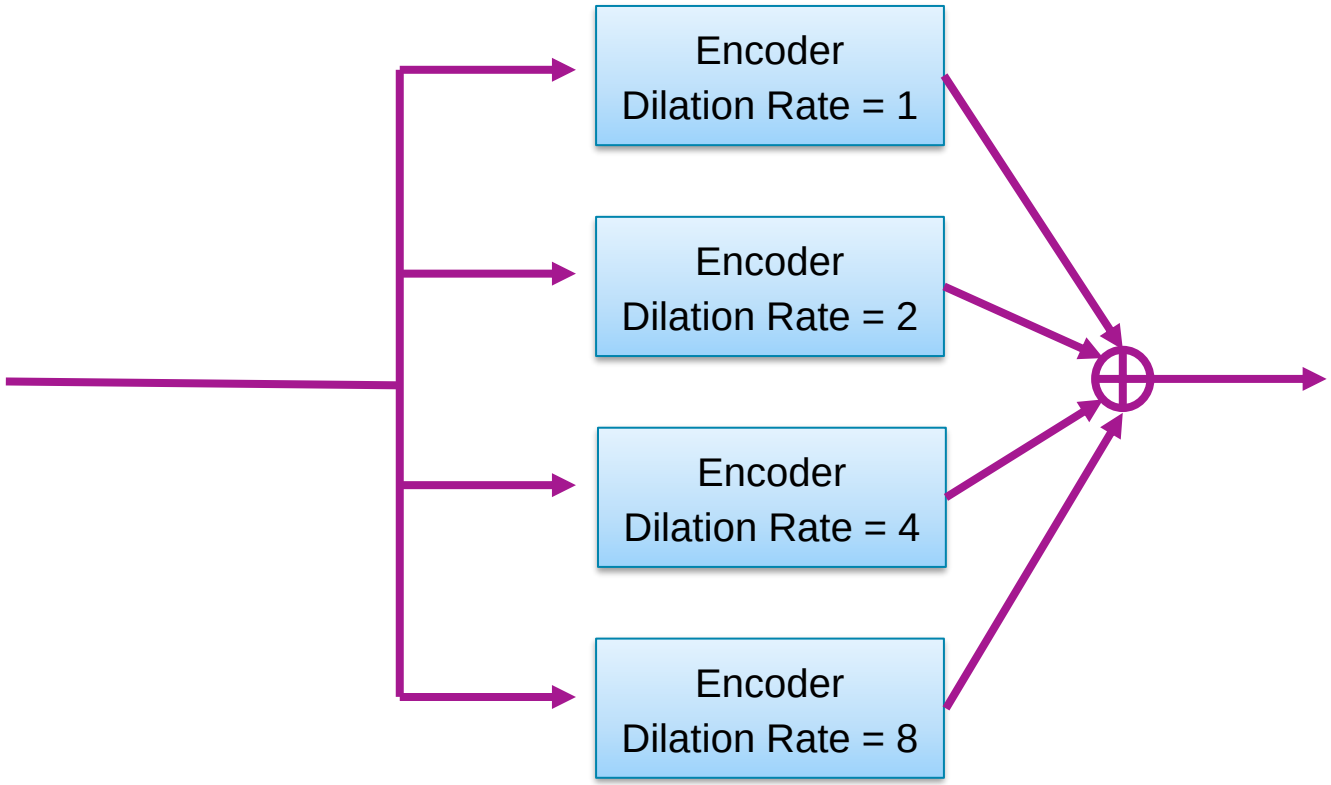
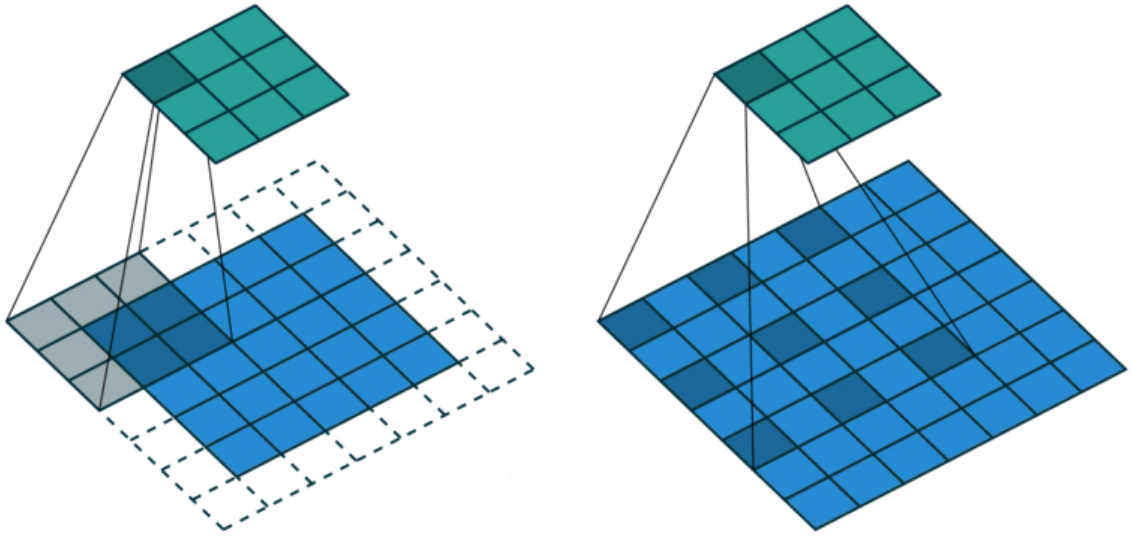
Unet: Serial Dilated Center (like DeepLab)

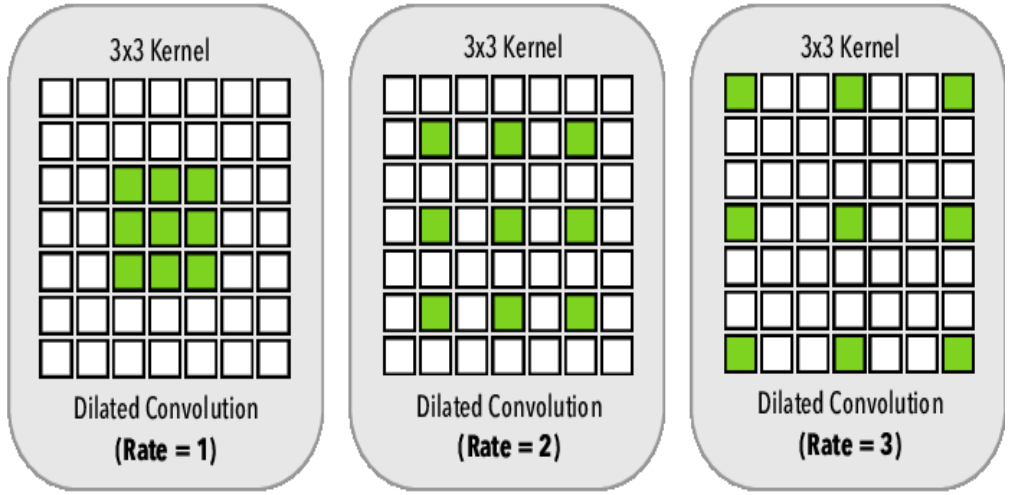


Unet: Parallel Dilated Center (like DeepLab)



Dilated Convolution Layer





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Tensorboard Experiment Results

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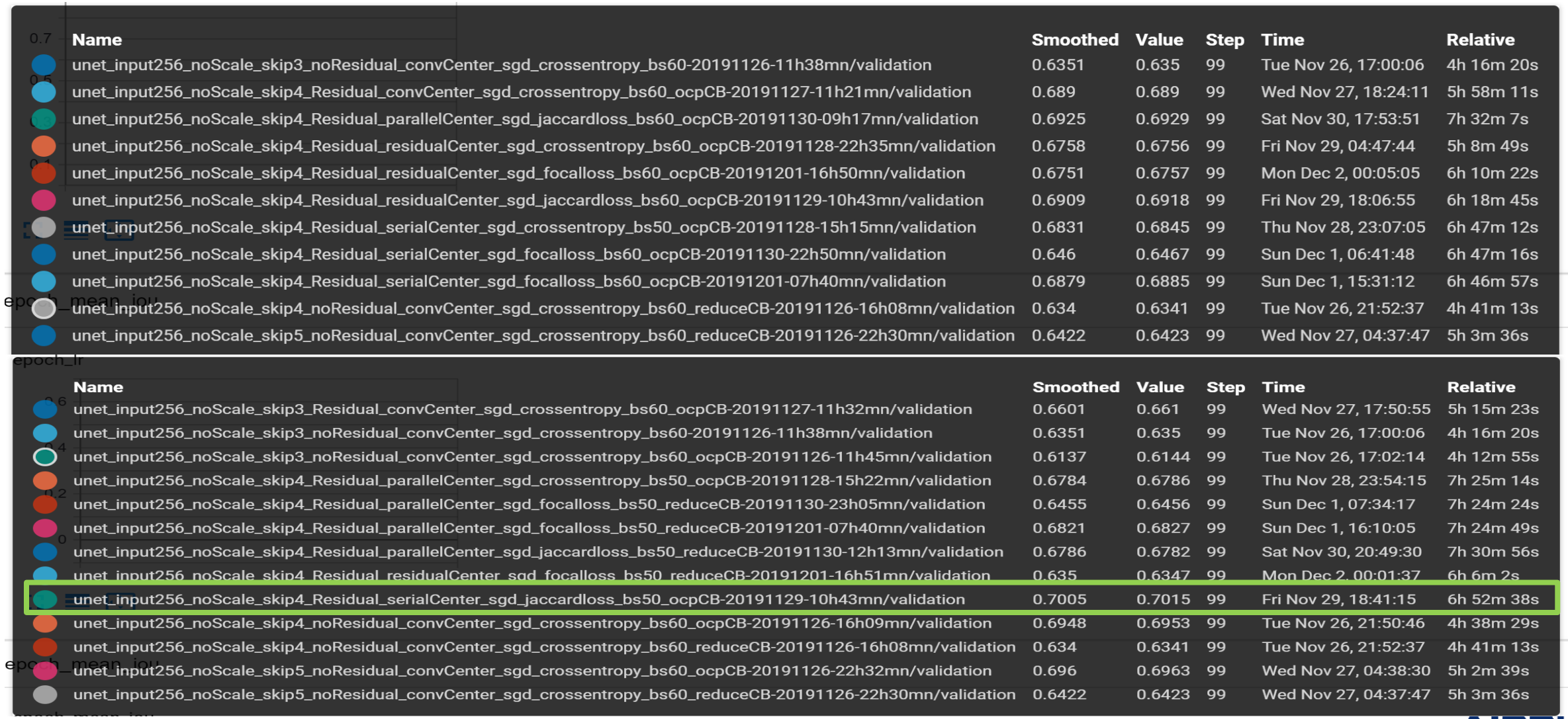
Experiment Results



Name	Smoothed	Value	Step	Time	Relative
unet_input256_noScale_skip3_noResidual_convCenter_sgd_crossentropy_bs60-20191126-11h38mn/validation	0.6351	0.635	99	Tue Nov 26, 17:00:06	4h 16m 20s
unet_input256_noScale_skip4_Residual_convCenter_sgd_crossentropy_bs60_ocpCB-20191127-11h21mn/validation	0.689	0.689	99	Wed Nov 27, 18:24:11	5h 58m 11s
unet_input256_noScale_skip4_Residual_parallelCenter_sgd_jaccardloss_bs60_ocpCB-20191130-09h17mn/validation	0.6925	0.6929	99	Sat Nov 30, 17:53:51	7h 32m 7s
unet_input256_noScale_skip4_Residual_residualCenter_sgd_crossentropy_bs60_ocpCB-20191128-22h35mn/validation	0.6758	0.6756	99	Fri Nov 29, 04:47:44	5h 8m 49s
unet_input256_noScale_skip4_Residual_residualCenter_sgd_focalloss_bs60_ocpCB-20191201-16h50mn/validation	0.6751	0.6757	99	Mon Dec 2, 00:05:05	6h 10m 22s
unet_input256_noScale_skip4_Residual_residualCenter_sgd_jaccardloss_bs60_ocpCB-20191129-10h43mn/validation	0.6909	0.6918	99	Fri Nov 29, 18:06:55	6h 18m 45s
unet_input256_noScale_skip4_Residual_serialCenter_sgd_crossentropy_bs50_ocpCB-20191128-15h15mn/validation	0.6831	0.6845	99	Thu Nov 28, 23:07:05	6h 47m 12s
unet_input256_noScale_skip4_Residual_serialCenter_sgd_focalloss_bs60_ocpCB-20191130-22h50mn/validation	0.646	0.6467	99	Sun Dec 1, 06:41:48	6h 47m 16s
unet_input256_noScale_skip4_Residual_serialCenter_sgd_focalloss_bs60_ocpCB-20191201-07h40mn/validation	0.6879	0.6885	99	Sun Dec 1, 15:31:12	6h 46m 57s
unet_input256_noScale_skip4_noResidual_convCenter_sgd_crossentropy_bs60_reduceCB-20191126-16h08mn/validation	0.634	0.6341	99	Tue Nov 26, 21:52:37	4h 41m 13s
unet_input256_noScale_skip5_noResidual_convCenter_sgd_crossentropy_bs60_reduceCB-20191126-22h30mn/validation	0.6422	0.6423	99	Wed Nov 27, 04:37:47	5h 3m 36s

Name	Smoothed	Value	Step	Time	Relative
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unet_input256_noScale_skip3_noResidual_convCenter_sgd_crossentropy_bs60_ocpCB-20191126-11h45mn/validation	0.6137	0.6144	99	Tue Nov 26, 17:02:14	4h 12m 55s
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unet_input256_noScale_skip4_Residual_residualCenter_sgd_focalloss_bs50_reduceCB-20191201-16h51mn/validation	0.635	0.6347	99	Mon Dec 2, 00:01:37	6h 6m 2s
unet_input256_noScale_skip4_Residual_serialCenter_sgd_jaccardloss_bs50_ocpCB-20191129-10h43mn/validation	0.7005	0.7015	99	Fri Nov 29, 18:41:15	6h 52m 38s
unet_input256_noScale_skip4_noResidual_convCenter_sgd_crossentropy_bs60_ocpCB-20191126-16h09mn/validation	0.6948	0.6953	99	Tue Nov 26, 21:50:46	4h 38m 29s
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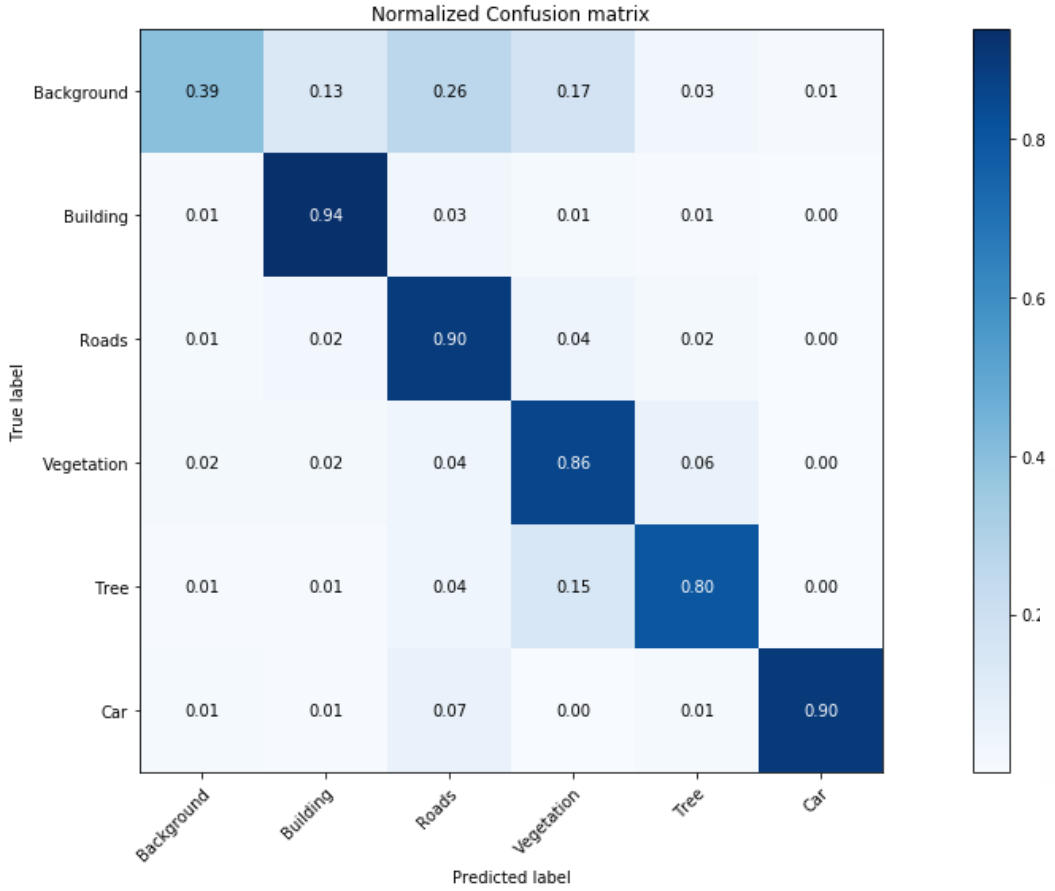
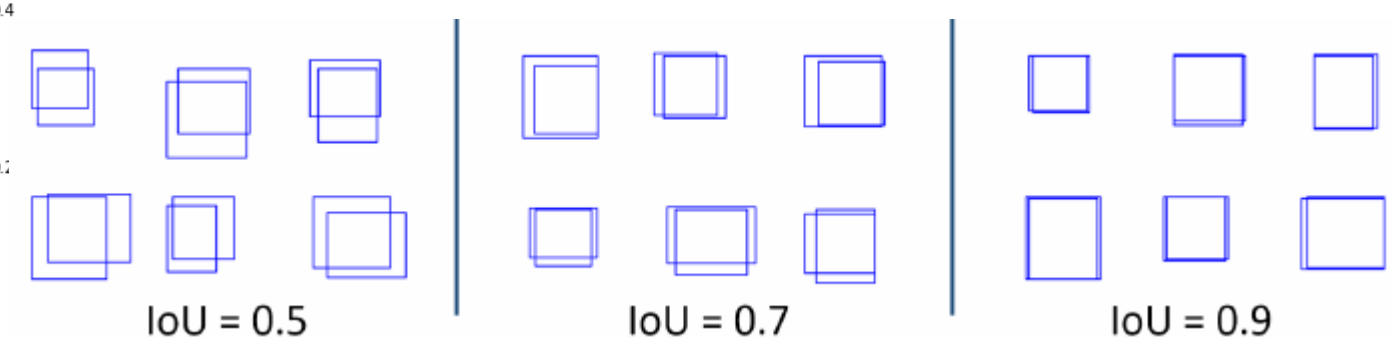
unet_input256_noScale_skip5_noResidual_convCenter_sgd_crossentropy_bs60_ocpCB-20191126-22h32mn/validation	0.696	0.6963	99	Wed Nov 27, 04:38:30	5h 2m 39s
unet_input256_noScale_skip5_noResidual_convCenter_sgd_crossentropy_bs60_reduceCB-20191126-22h30mn/validation	0.6422	0.6423	99	Wed Nov 27, 04:37:47	5h 3m 36s

Best Model Detailed Results Computed on Validation Set



Background	Building	Roads	Vegetation	Tree	Car
0.3132	0.8701	0.8030	0.6928	0.7061	0.8243

Validation Dataset Jaccard Index (IoU) per Class



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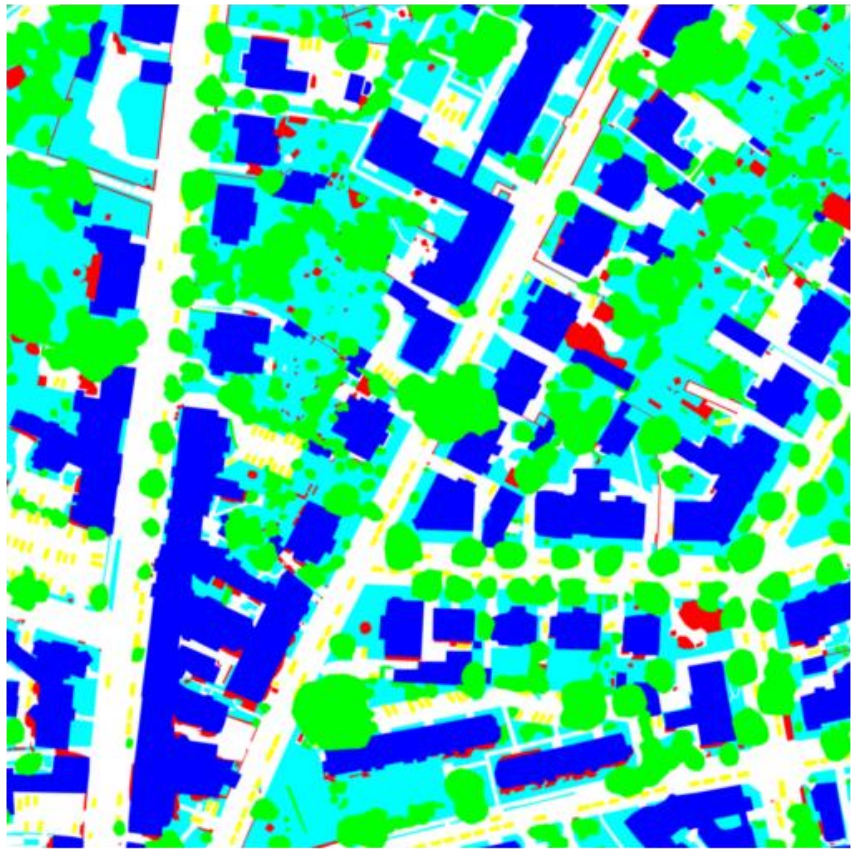
Predicting on a new Tile (from Validation set)

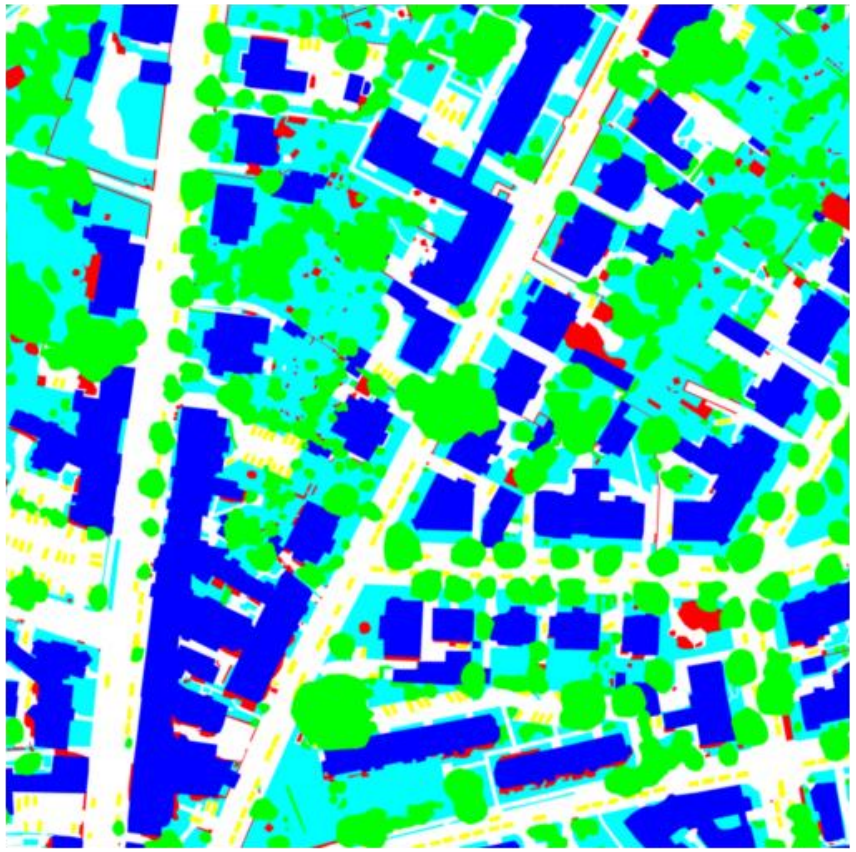
Aerial Tile

Reference Mask

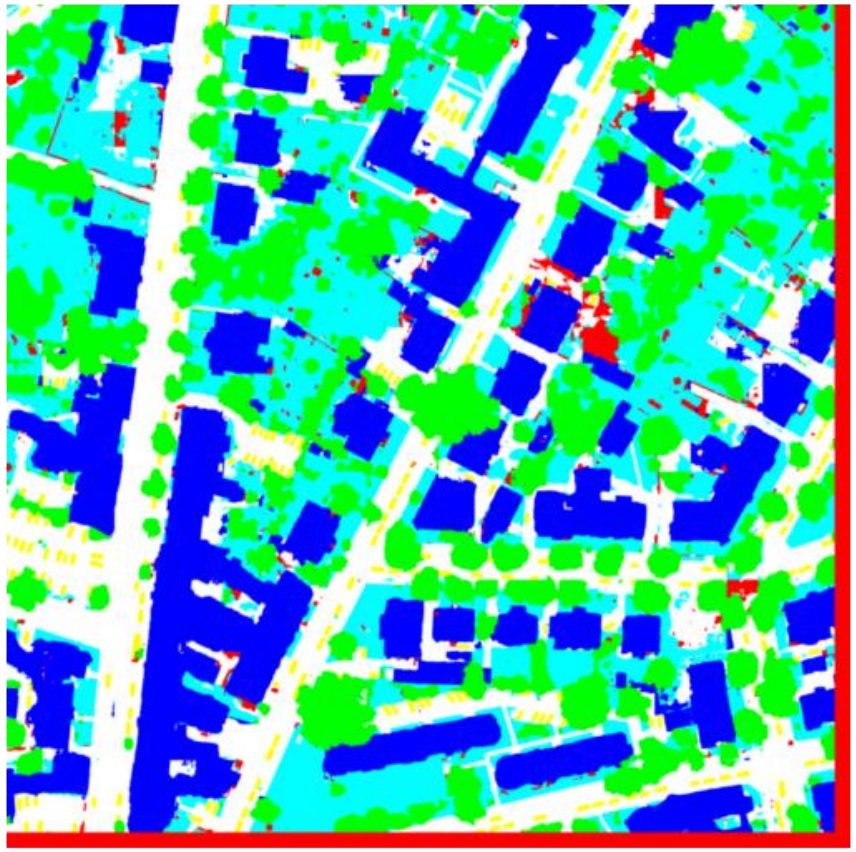


Predicting on a new Tile (from Validation set)

Reference Mask



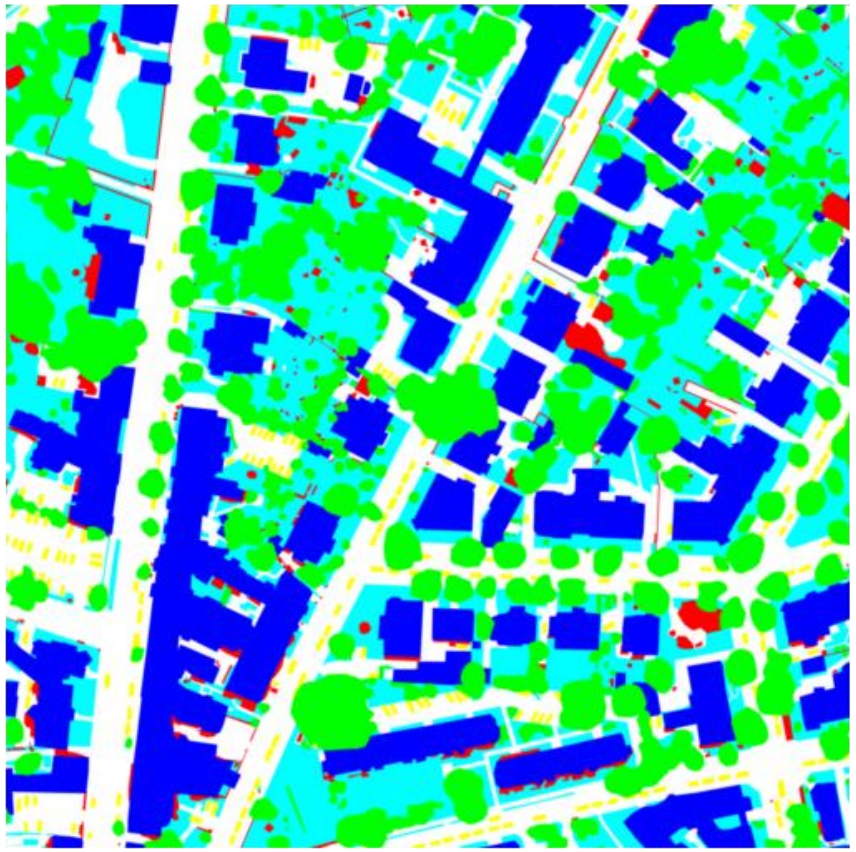
Prediction



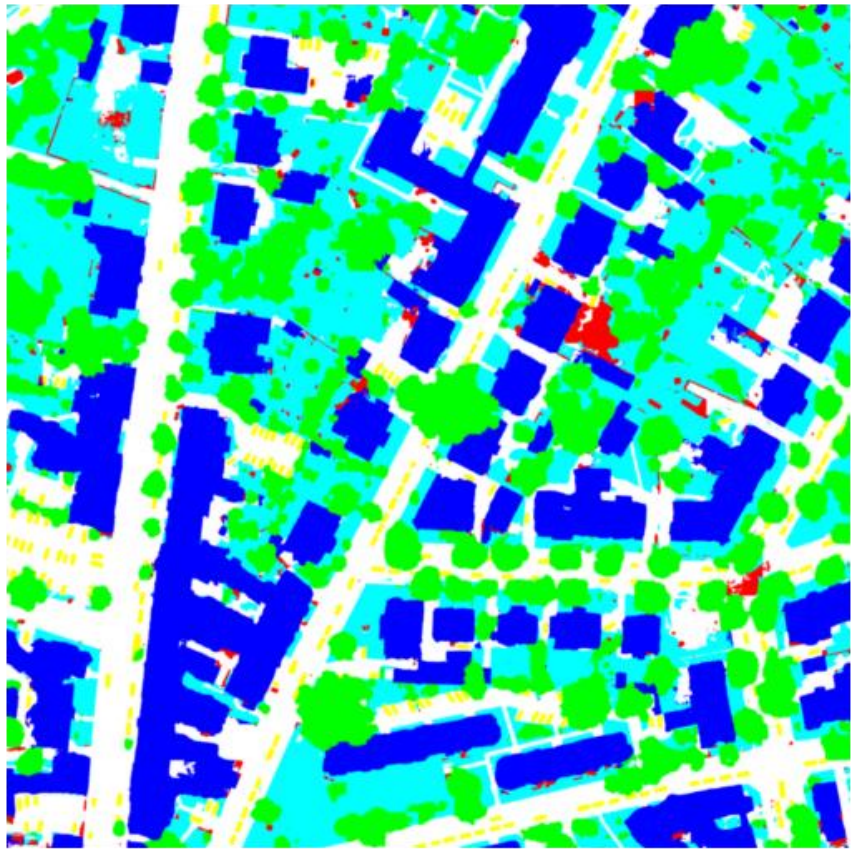
Background	Building	Roads	Vegetation	Tree	Car
0.1141	0.8755	0.7486	0.6756	0.7393	0.8093

Predicting on a new Tile with Test Time Augmentation

Reference Mask



Prediction

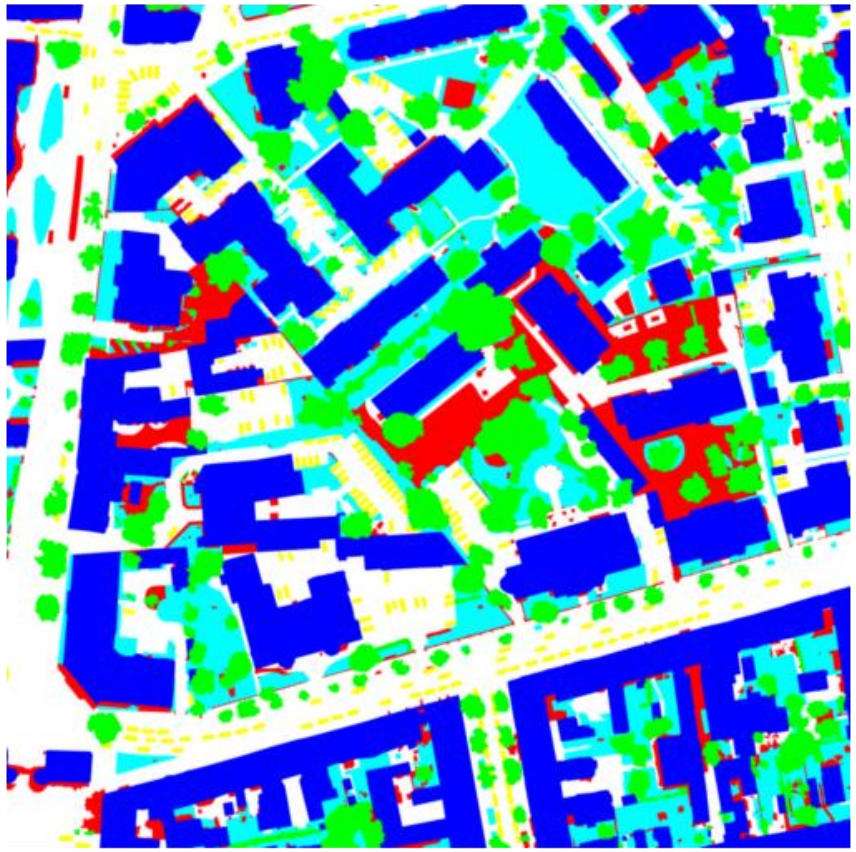


Background	Building	Roads	Vegetation	Tree	Car
0.2250	0.9143	0.7920	0.7171	0.7769	0.8416

Predicting on a new Tile (Example 2)

Aerial Tile

Reference Mask



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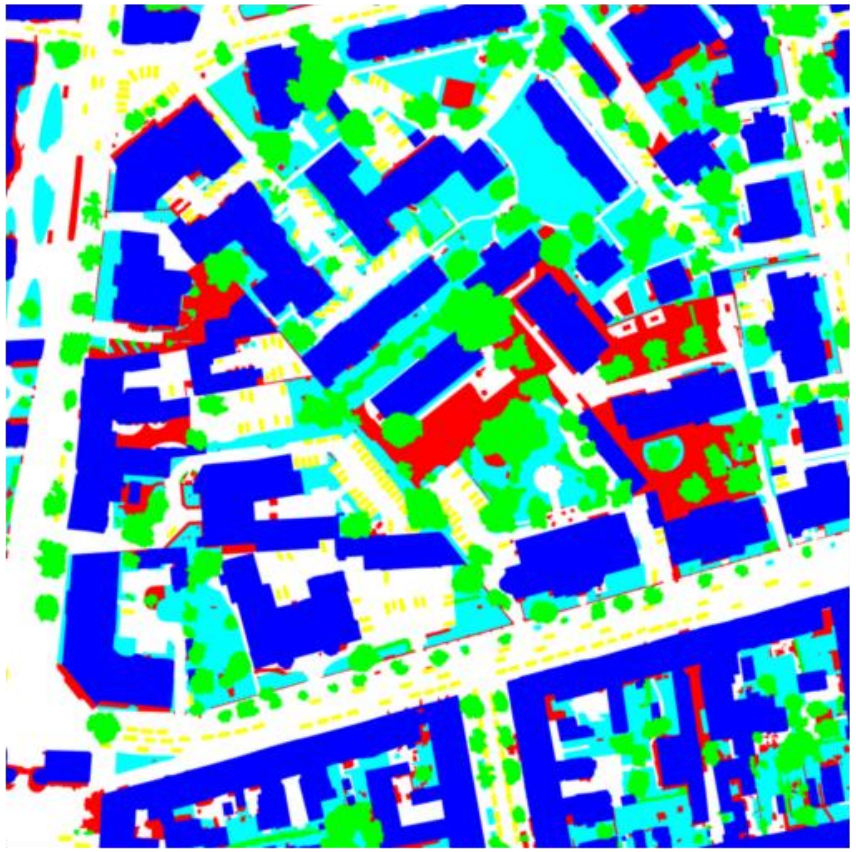
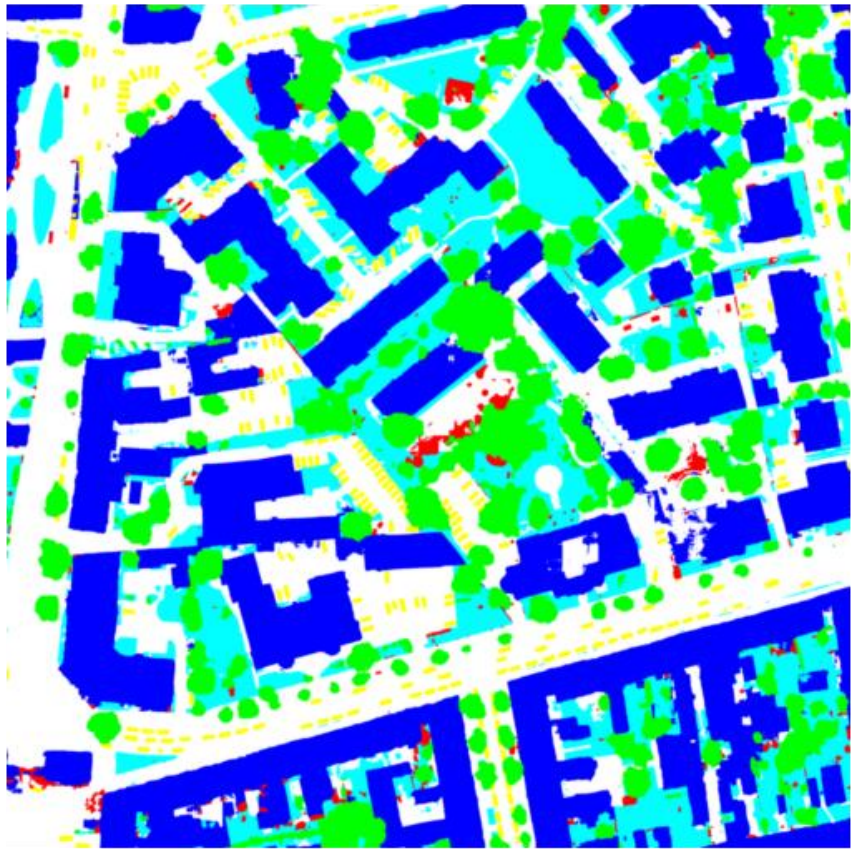
Predicting on a new Tile (Example 2)

Reference Mask



Prediction

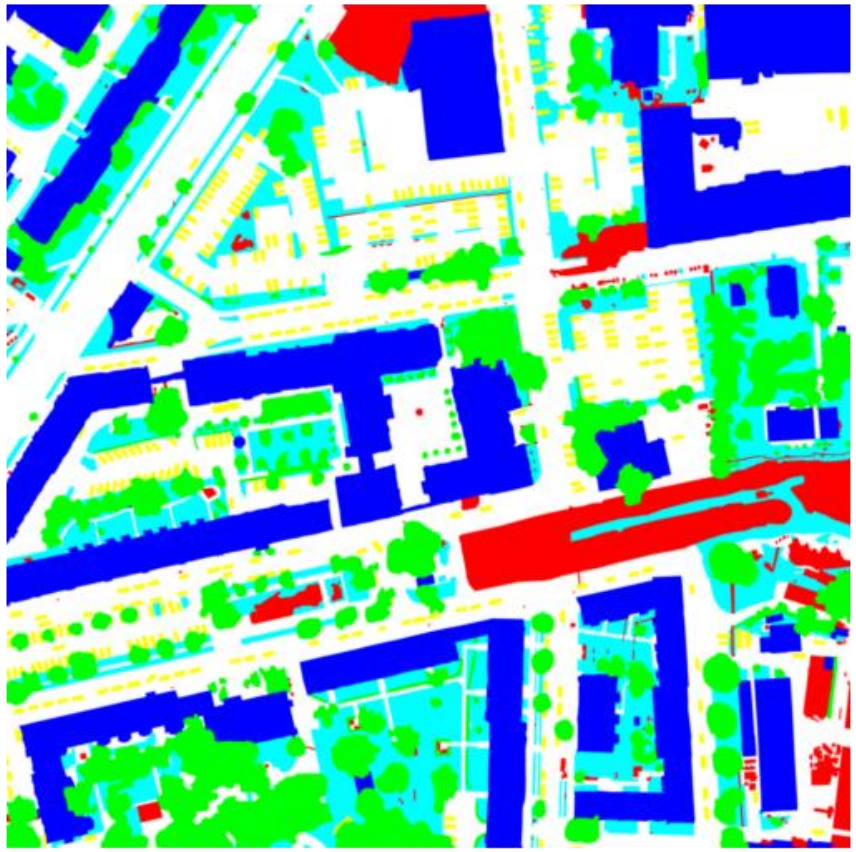


Background	Building	Roads	Vegetation	Tree	Car
0.1259	0.9212	0.7887	0.6878	0.7341	0.8615

Predicting on a new Tile (Example 3)

Aerial Tile

Reference Mask



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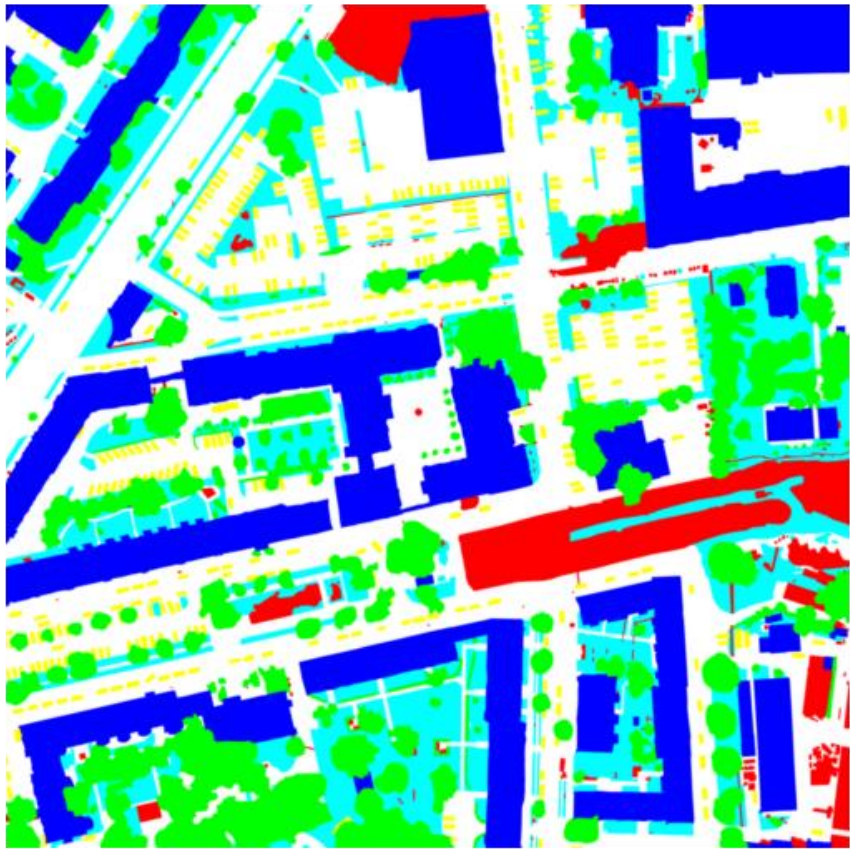
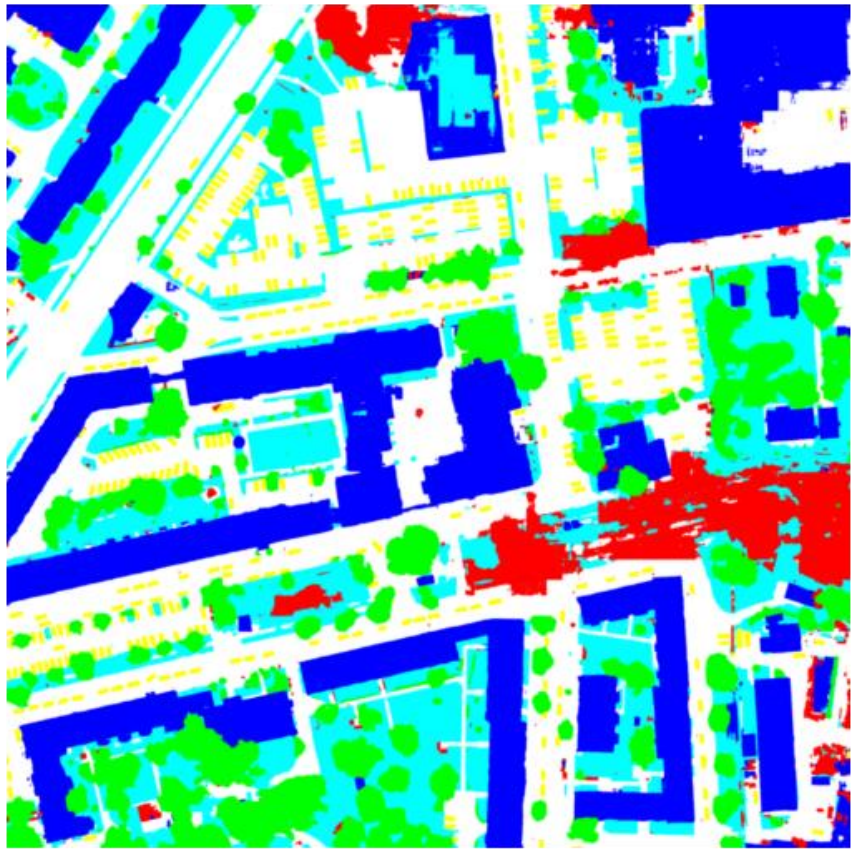
Predicting on a new Tile (Example 3)

Reference Mask



Prediction



Background	Building	Roads	Vegetation	Tree	Car
0.5344	0.8806	0.8454	0.6298	0.7001	0.8502

Model into the wild

Divider subtitle

Predicting on Marseille

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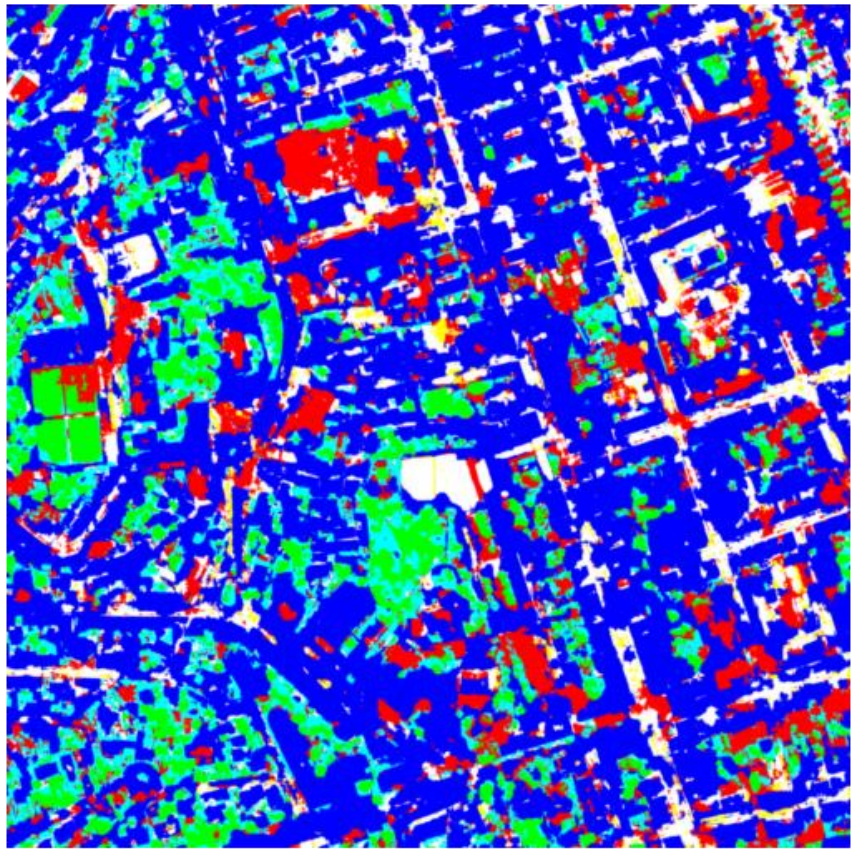
Predicting on Marseille

Aerial Tile

Prediction



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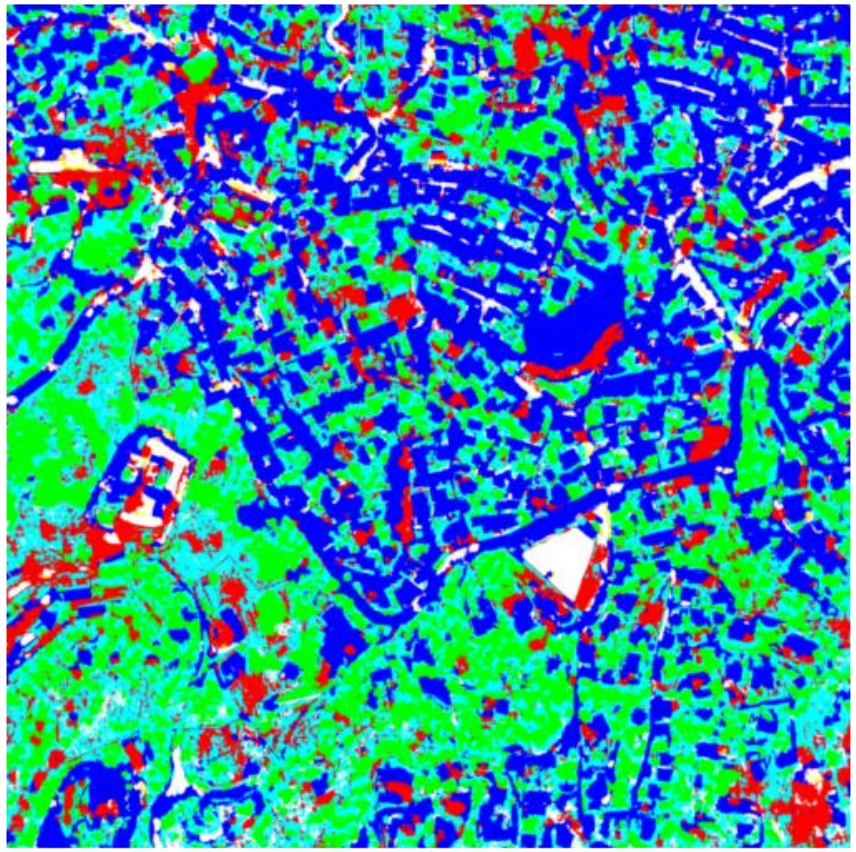
Predicting on Marseille

Aerial Tile

Prediction



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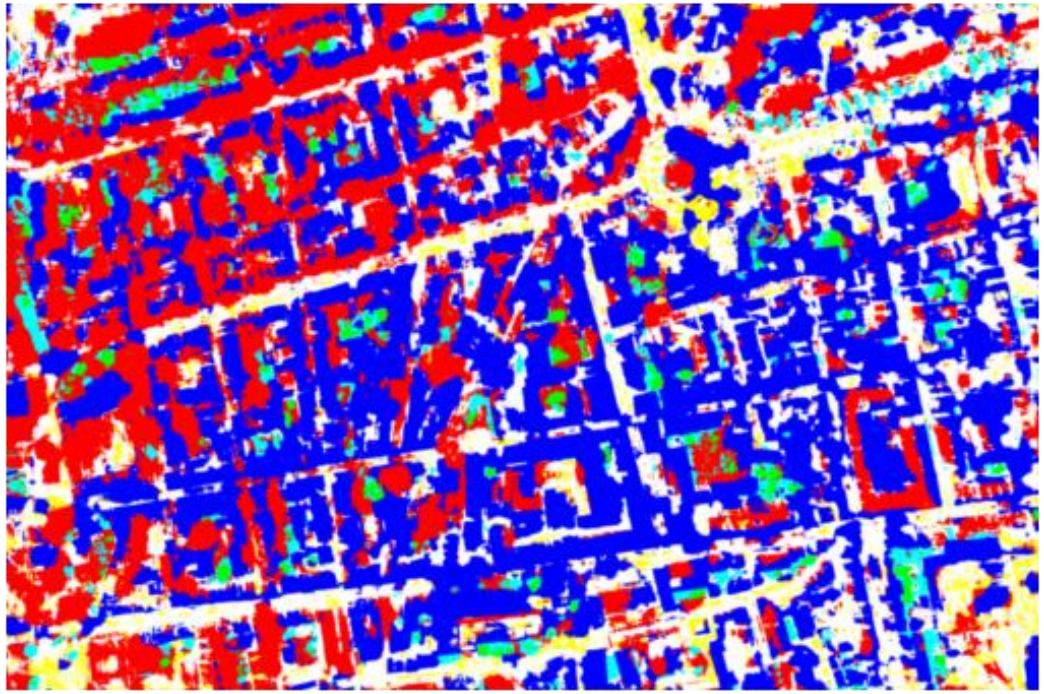
Predicting on Toulouse (NADIR)

Aerial Tile

Prediction



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What Happened ?

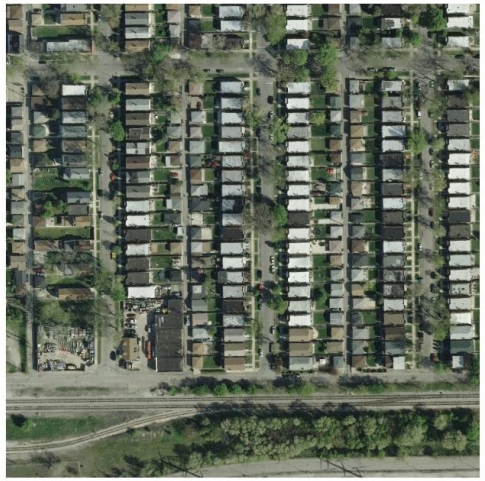
- Our Model did not generalize well.

- Possible root causes:
  - Training set is too small: limited to one city, tile resolution
  - Implemented Data Augmentation is limited: need more
  - Inference tile have challenging lightning aspects
  - Off-Nadir images does not provide good results

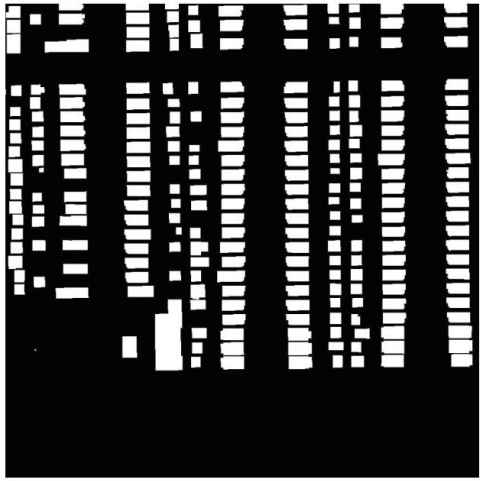
INRIA Aerial Building Dataset

INRIA Building Dataset

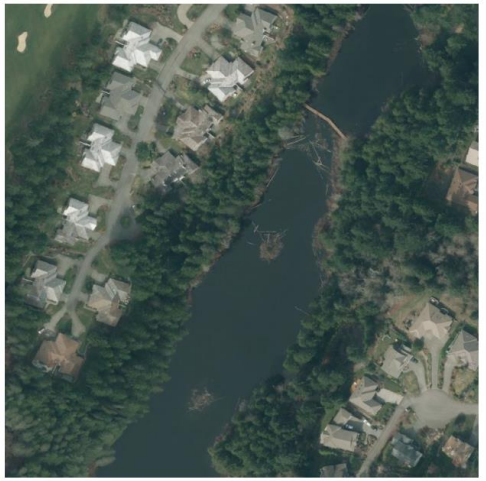
- The training set contains 180 color image tiles of size 5000×5000, covering a surface of 1500 m × 1500 m each (at a 30 cm resolution).
- There are 36 tiles for each of the following regions:
  - Austin
  - Chicago
  - Kitsap County
  - Western Tyrol
  - Vienna



Chicago



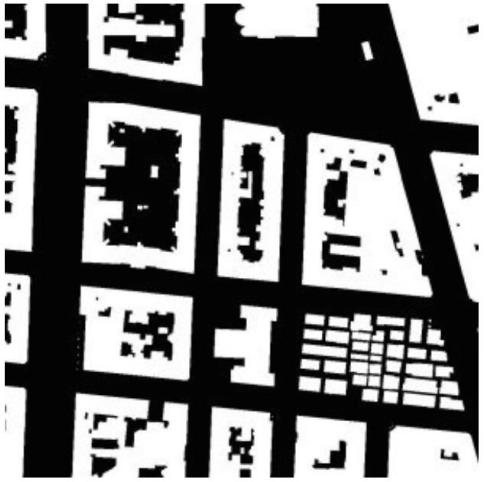
Chicago – reference



Kitsap County, WA

Kitsap County, WA – Reference

Vienna



Vienna – Reference

INRIA: Defining the Train and the Validation dataset objects

[20]:
```
train_ds = get_dataset(img_dir=inria_train_img_dir, mask_dir=inria_train_mask_dir, batch_size=BATCH_SIZE, shuffle=True, repeat=True, augment=True, cachefile='inria_train_cache')
val_ds   = get_dataset(img_dir=inria_val_img_dir, mask_dir=inria_val_mask_dir,batch_size=BATCH_SIZE, shuffle=False, repeat=True, augment=False, cachefile=None)
print("train patch number = {}, valid patch number = {}".format(TRAIN_PATCH_NUMBER, VALID_PATCH_NUMBER))
print("train steps = {}, valid steps = {}".format(TRAIN_STEPS_PER_EPOCH, VAL_STEPS_PER_EPOCH))
```

```
Removing old cache file: /tmp/inria_train_cache.index
Removing old cache file: /tmp/inria_train_cache.data-00000-of-00001
train patch number = 361, valid patch number = 361
train steps = 1120, valid steps = 181
```

[22]:
```
timepipeline(train_ds, batch_size=BATCH_SIZE, steps=4000)
```

Error displaying widget: model not found

```
batche size: 50
4000 batches: 414.9433560371399 s
9.63987 Batches/s
481.99350 Images/s
```

[28]:
```
timepipeline(val_ds, batch_size=BATCH_SIZE, steps=1000)
```

Error displaying widget: model not found

```
batche size: 50
1000 batches: 41.72989892959595 s
23.96363 Batches/s
1198.18167 Images/s
```

INRIA: Defining the Model

[47]:
```
inria_model = get_unet_model(MODEL_SHAPE, filters=32, n_block=4, n_class=2, mode=None, residual=True)
inria_model.summary()
```

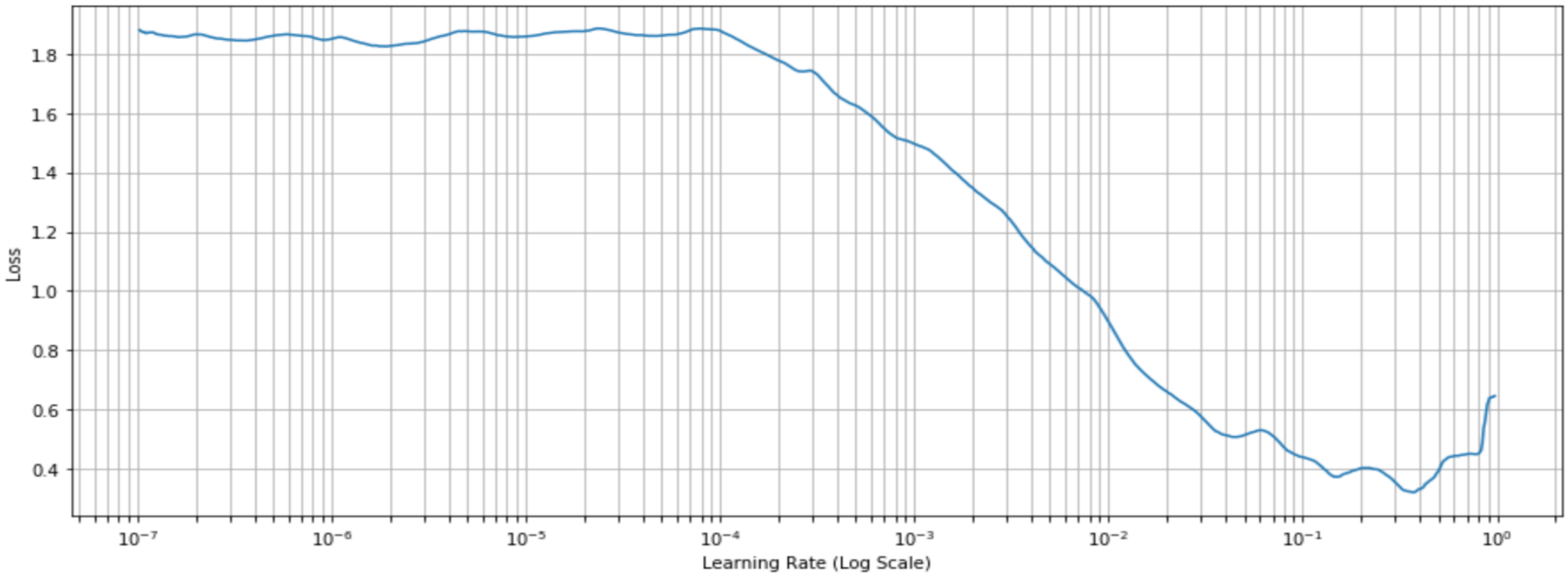
```
Total params: 10,730,984
Trainable params: 10,725,096
Non-trainable params: 5,888
```

[ ]:
```
experiment_name = "inria_unet_input256_noScale_skip4_Residual_residualCenter_sgd_cross_entropy_bs50_ocpCB"
sgd_optim = tf.keras.optimizers.SGD(lr=0.1, nesterov=True)
acc_metric = tf.keras.metrics.SparseCategoricalAccuracy(name='Accuracy')
iou_metric = tf.keras.metrics.MeanIoU(num_classes=NUM_CLASSES)
fixed_iou  = CategoricalMeanIoU(num_classes=NUM_CLASSES)
inria_model.compile(optimizer=sgd_optim, loss='sparse_categorical_crossentropy', metrics=[acc_metric,fixed_iou])
```

INRIA: Finding the Learning Rate

[41]:
```
lrf = LearningRateFinder(inria_model)
lrf.find(train_ds, 1e-7, 1, epochs=1, stepsPerEpoch=TRAIN_STEPS_PER_EPOCH)
lrf.plot_loss()
```

```
Train for 1120 steps
1120/1120 [==============================] - 794s 709ms/step - loss: 1.3063 - Accuracy: 0.6399 - mean_iou: 0.3948
```



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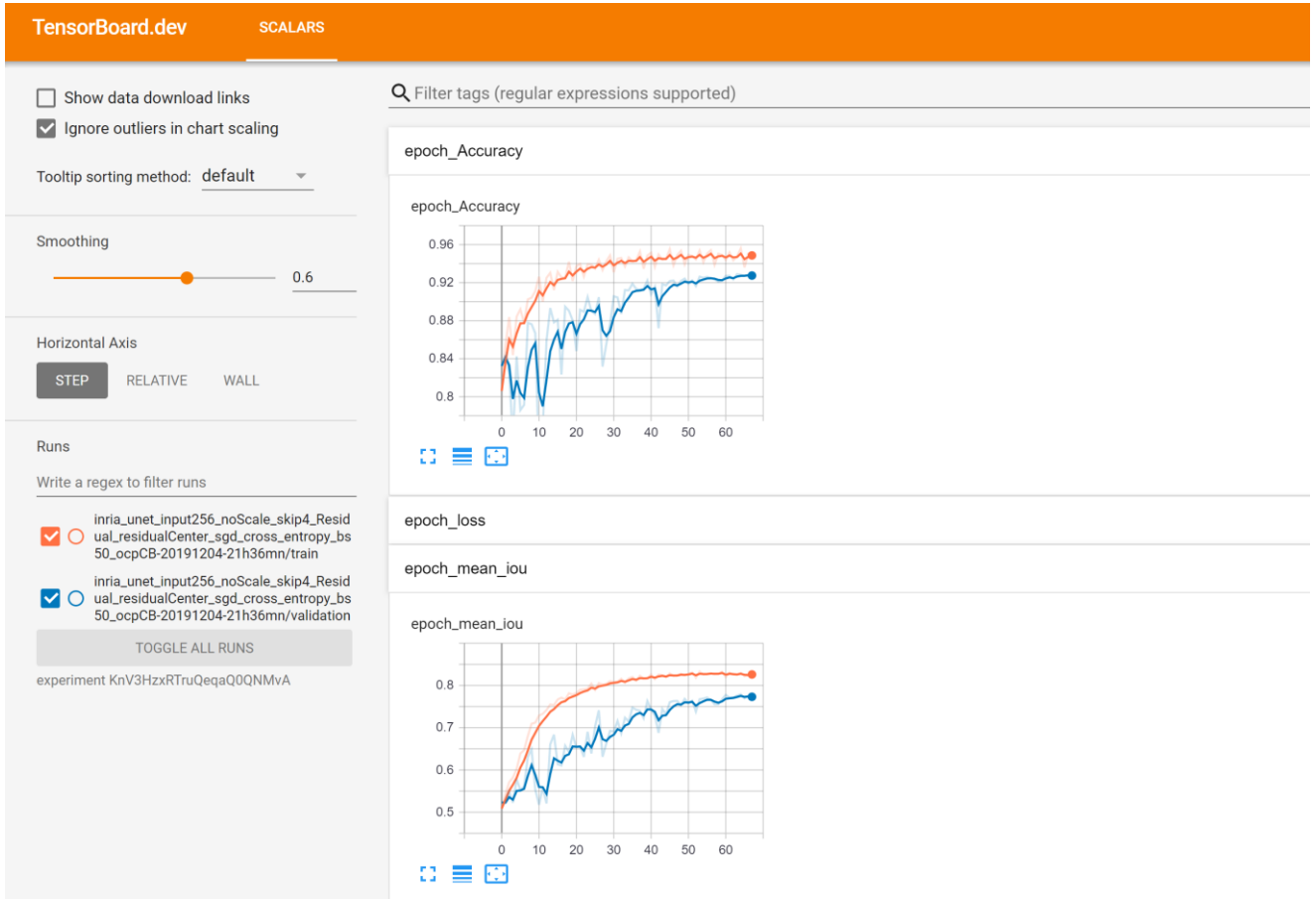
INRIA: Training Phase

[ ]:
```
# One cycle policy training
checkpoint_path = "../inria_checkpoint_dir/" + experiment_name + datetime.now().strftime("-%Y%m%d-%Hh%Mmn") + "/best-cp-" + experiment_name
tb_log_dir      = "../inria_log_dir/" + experiment_name + datetime.now().strftime("-%Y%m%d-%Hh%Mmn")
# callbacks
ocp_cb = OneCycleScheduler(max_lr=1e-1)
checkpoint_cb  = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_path, monitor='val_mean_iou', mode='max', save_weights_only=True, save_best_only=True, verbose=1)
tensorboard_cb = tf.keras.callbacks.TensorBoard(log_dir=tb_log_dir)

keras_history = inria_model.fit(train_ds,
                    steps_per_epoch=TRAIN_STEPS_PER_EPOCH,
                    epochs=70,
                    validation_data=val_ds,
                    validation_steps=VAL_STEPS_PER_EPOCH,
                    callbacks=[ocp_cb, checkpoint_cb, tensorboard_cb],
                    verbose=1)
```

```
Train for 1120 steps, validate for 181 steps
Epoch 1/70
1119/1120 [============================>.] - ETA: 0s - loss: 0.5033 - Accuracy: 0.8061 - mean_iou: 0.5086 - OneCycleScheduler, lr: 0.0045361, momentum: 0.9491623

Epoch 00001: val_mean_iou improved from -inf to 0.52302, saving model to ../inria_checkpoint_dir/inria_unet_input256_noScale_skip4_Residual_residualCenter_sgd_cross_entropy_bs50_ocpCB-2019
esidual_residualCenter_sgd_cross_entropy_bs50_ocpCB
1120/1120 [==============================] - 833s 744ms/step - loss: 0.5031 - Accuracy: 0.8062 - mean_iou: 0.5086 - val_loss: 0.4252 - val_Accuracy: 0.8324 - val_mean_iou: 0.5230
Epoch 2/70
1119/1120 [============================>.] - ETA: 0s - loss: 0.3631 - Accuracy: 0.8538 - mean_iou: 0.5426 - OneCycleScheduler, lr: 0.0061325, momentum: 0.9466680

Epoch 00002: val_mean_iou did not improve from 0.52302
1120/1120 [==============================] - 830s 741ms/step - loss: 0.3631 - Accuracy: 0.8538 - mean_iou: 0.5426 - val_loss: 0.3866 - val_Accuracy: 0.8473 - val_mean_iou: 0.5223
Epoch 3/70
 296/1120 [======>.......................] - ETA: 9:31 - loss: 0.3196 - Accuracy: 0.8729 - mean_iou: 0.5586
```

INRIA: Monitoring the Training Phase



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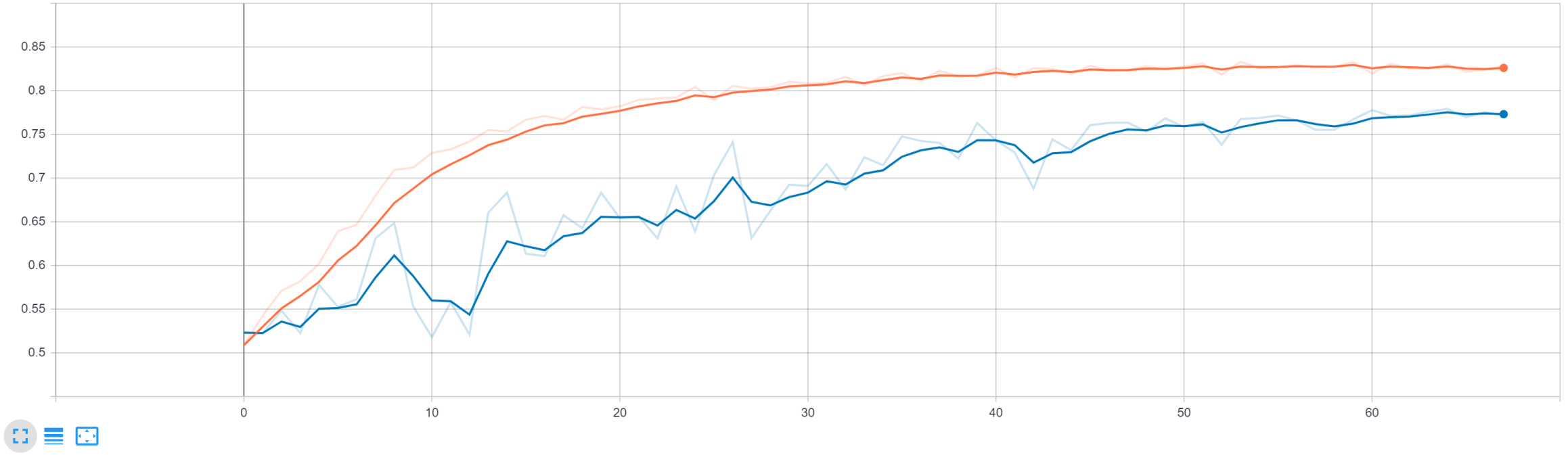
INRIA: Monitoring the Training Phase

epoch_loss

epoch_mean_iou

Name	Smoothed	Value	Step	Time	Relative
inria_unet_input256_noScale_skip4_Residual_residualCenter_sgd_cross_entropy_bs50_ocpCB-20191204-21h36mn/train	0.8261	0.828	67	Thu Dec 5, 14:18:31	15h 28m 13s
inria_unet_input256_noScale_skip4_Residual_residualCenter_sgd_cross_entropy_bs50_ocpCB-20191204-21h36mn/validation	0.7731	0.7718	67	Thu Dec 5, 14:18:31	15h 28m 13s

epoch_mean_iou



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INRIA: Evaluation

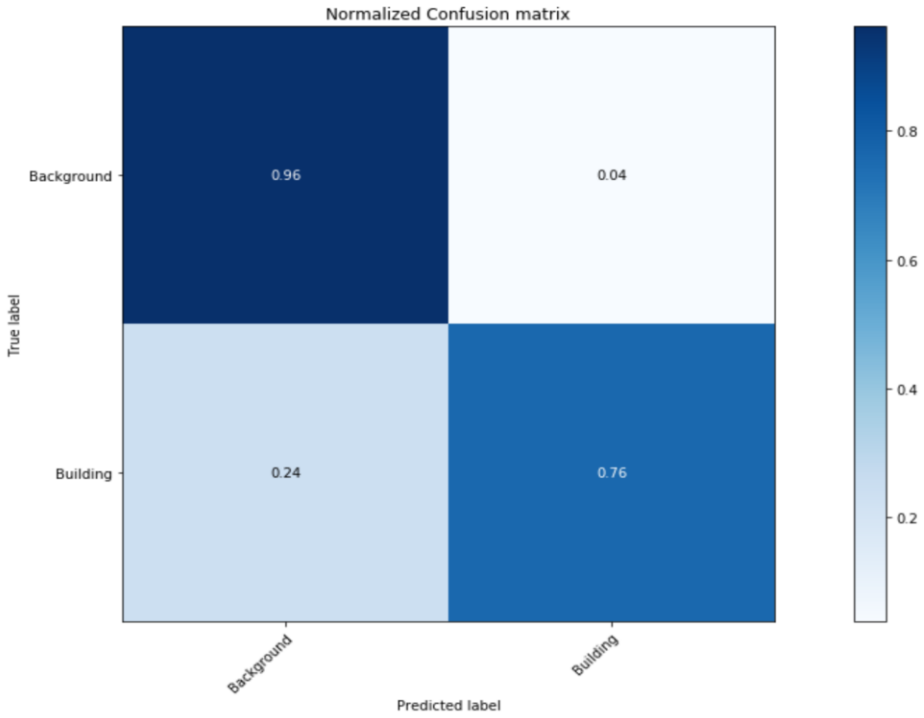
```
[ ]: inria_model.load_weights('../inria_checkpoint_dir/.../best-cp-inria_unet_input256_noScale_skip4_Residual_residualCenter_sgd_cross_entropy_bs50_ocpCB')
```

```
[46]: inria_model.evaluate(val_ds, steps=VAL_STEPS_PER_EPOCH)
```

```
181/181 [==============================] - 53s 293ms/step - loss: 0.1810 - Accuracy: 0.9283 - mean_iou: 0.7791
[46]: [0.1810000821824561, 0.92829496, 0.77909243]
```

```
[50]: compute_dataset_iou(inria_model, val_ds, VAL_STEPS_PER_EPOCH)
```

Error displaying widget: model not found



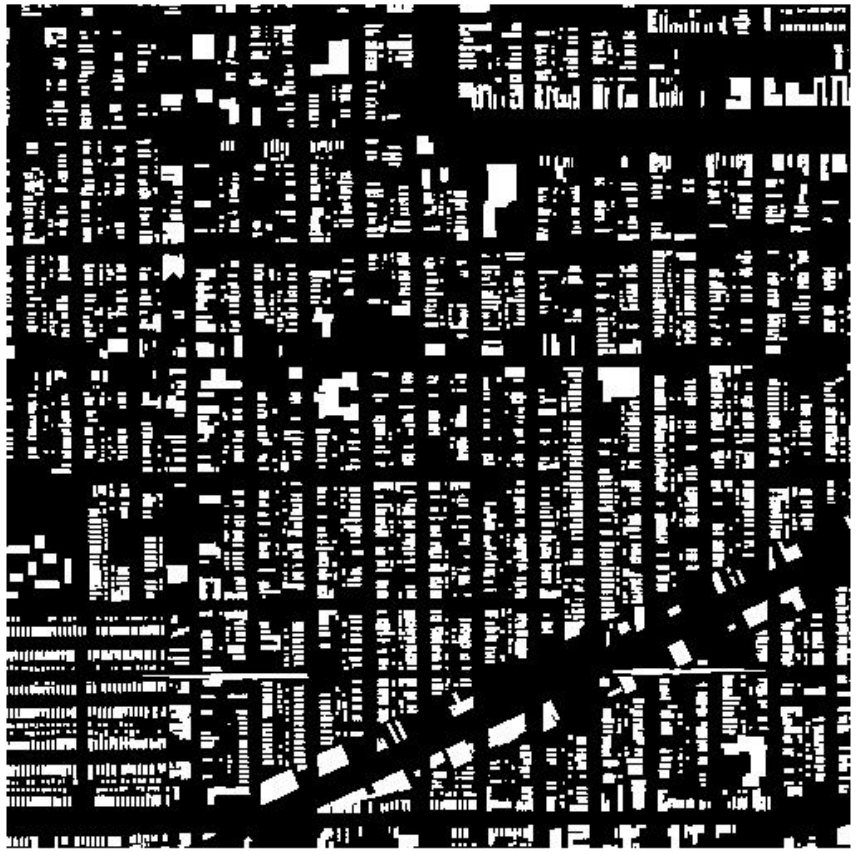
[50]:

	Background	Building
0	0.9178	0.6404

INRIA: predicting on a Validation tile (chicago)

Aerial Tile

Reference Mask



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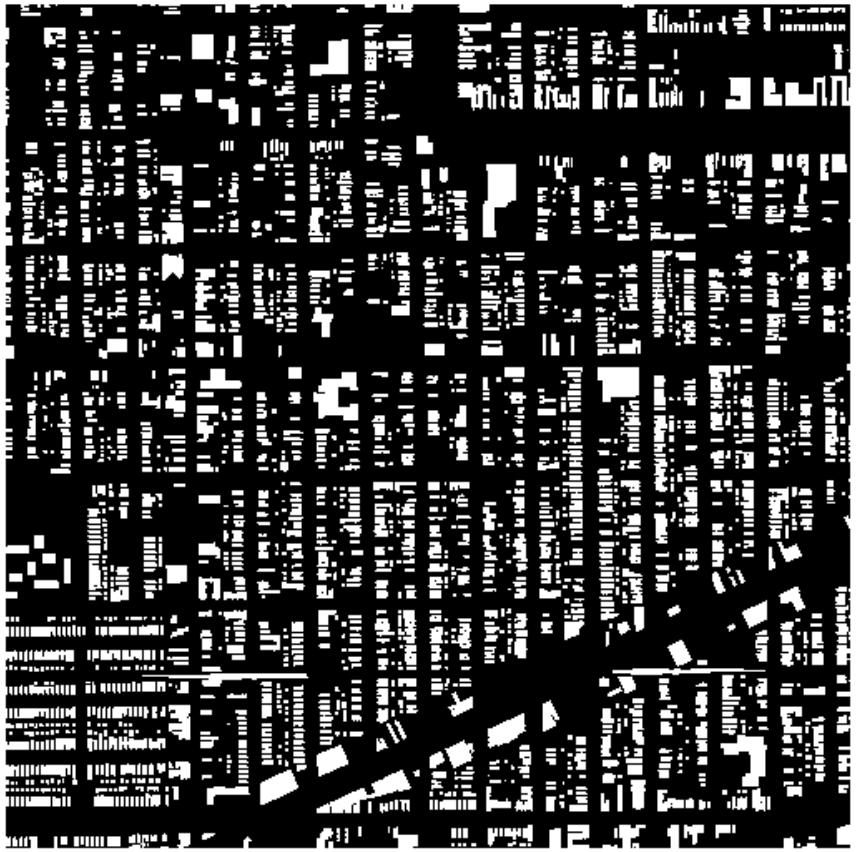
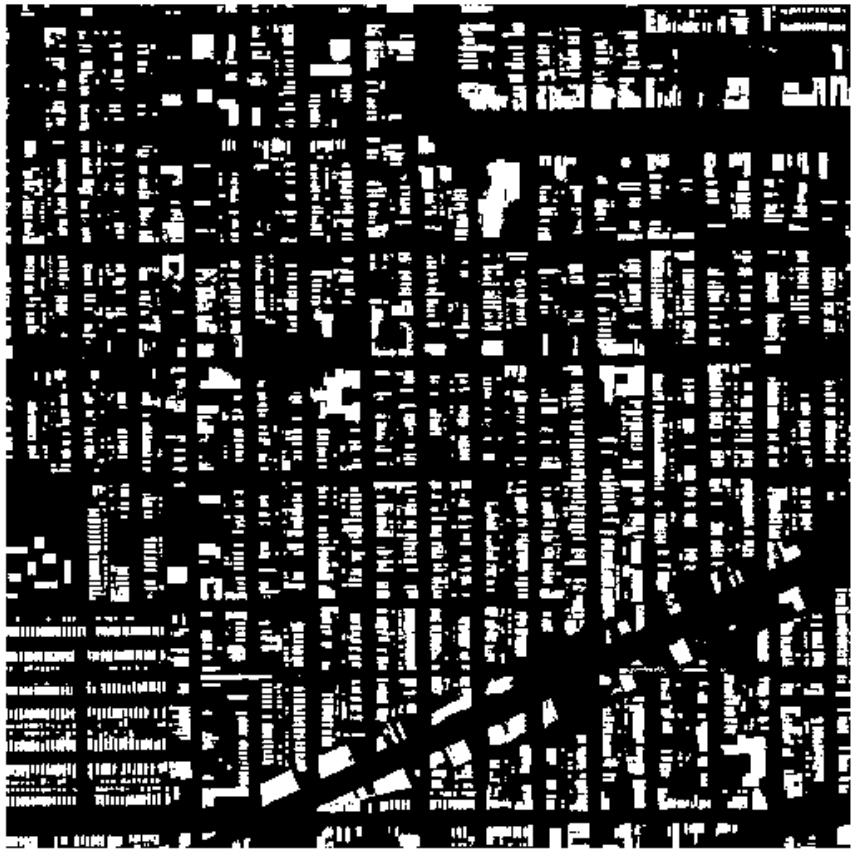
INRIA: predicting on a Validation tile (chicago)

Reference Mask



Prediction



```
[159]: get_tile_iou(msk, y_pred2)
```

[159]:

	Background	Building
0	0.8908	0.6419

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INRIA: Predicting on Marseille

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INRIA: Predicting on Marseille

Aerial Tile

Prediction

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INRIA: Predicting on Marseille (oblique image)

Aerial Tile

Prediction

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Conclusion

- Produced a fast, flexible and robust input pipeline that make optimal usage of CPU & GPU resources
- Trained Deep learning Neural Network for segmentation with transparent performance metrics and reproductible flow
- Tried cutting-edge research technique to train neural networks (learning rate finder, One Cycle Policy)
- Tried New Loss function (Focal Loss, Jaccard Index Loss)
- Reached state of the Art results on the ISPRS dataset
- Learned (the hard way) that Model Performance is tightly coupled with its training data: Variety and Quantity are paramount

Where to go from here

- Synthetic datasets: Generative model for data augmentation
- Combine Geometric Computer vision with Deep Learning
- Prediction post processing

Bibliography

- **UNet: Convolutional Networks for Biomedical Image Segmentation:** https://arxiv.org/abs/1505.04597
- **Cyclical Learning Rates for Training Neural Networks:** https://arxiv.org/abs/1506.01186
- **A disciplined approach to neural network hyper-parameters: Part 1 learning rate, batch size, momentum, and weight decay:** https://arxiv.org/abs/1803.09820
- **Super-Convergence: Very Fast Training of Neural Networks Using Large Learning Rates:** https://arxiv.org/abs/1708.07120
- **Focal Loss for Dense Object Detection:** https://arxiv.org/abs/1708.02002
- **Deep Residual Learning for Image Recognition:** https://arxiv.org/abs/1512.03385
- **Densely Connected Convolutional Networks:** https://arxiv.org/abs/1608.06993
- **Semantic Labeling in Very High Resolution Images via a Self-Cascaded Convolutional Neural Network:** https://www.researchgate.net/publication/321970661_Semantic_Labeling_in_Very_High_Resolution_Images_via_a_Self-Cascaded_Convolutional_Neural_Network_ISPRS_JPRS_IF6942

Thank you