

Panoptic Segmentation on aerial Images in urban Area

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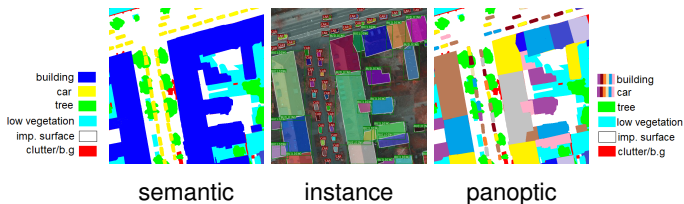
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Panoptic Segmentation

What is Panoptic Segmentation?



- countatble things vs. uncountable stuff.
- panoptic - including everything visible in one view.
- a unified framework combining instance segmentation & semantic segmentation.
- applications on automatic building map updating.
- lacking of datasets on aerial images.

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3 Panoptic Segmentation Model

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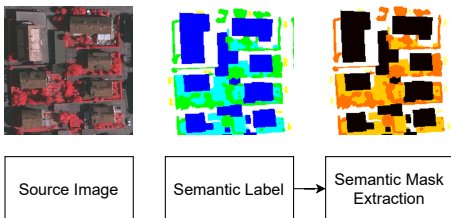
4 Experiments

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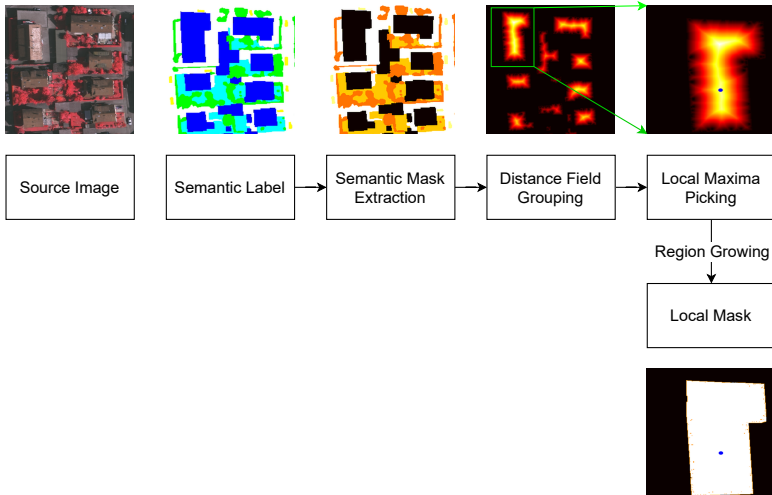
Dataset Annotation

From Semantic to Instance



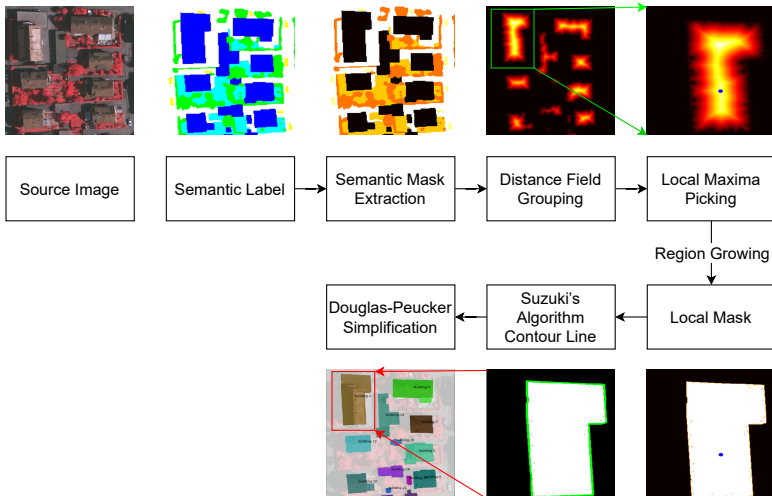
Dataset Annotation

From Semantic to Instance



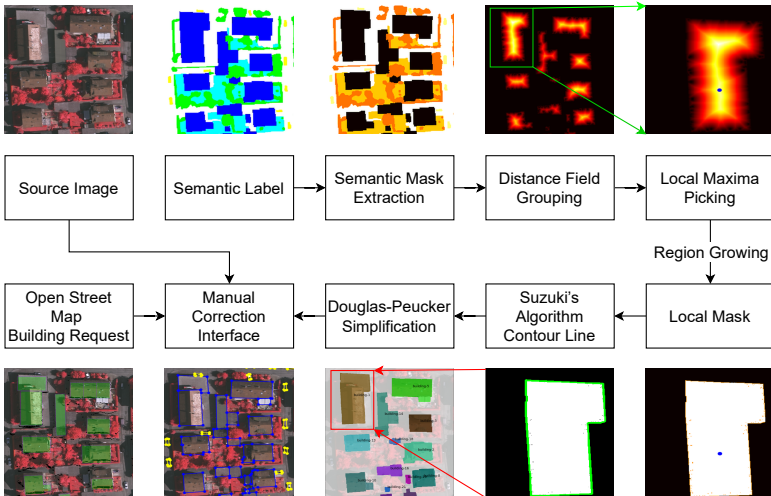
Dataset Annotation

From Semantic to Instance



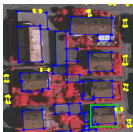
Dataset Annotation

From Semantic to Instance

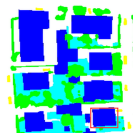


Dataset Annotation

From Instance/Semantic to Panoptic



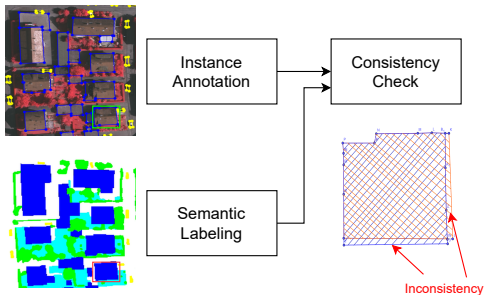
Instance Annotation



Semantic Labeling

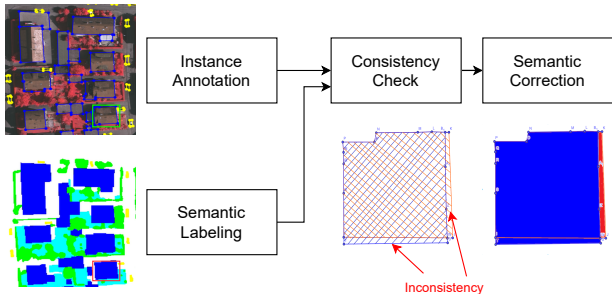
Dataset Annotation

From Instance/Semantic to Panoptic



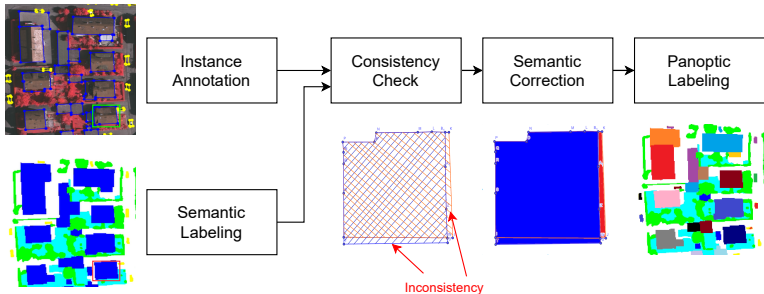
Dataset Annotation

From Instance/Semantic to Panoptic



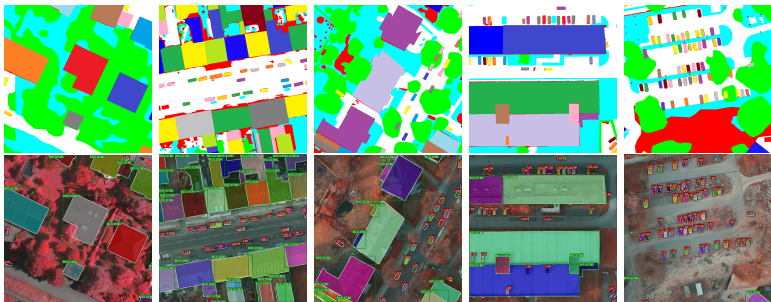
Dataset Annotation

From Instance/Semantic to Panoptic



PanUrban Dataset

Introduction



apartment

innercity

residual

factory

parking

- Subsets: Potsdam, Vaihingen, MA.
- Bounding boxes axis-aligned(ABB) or rotated(RBB).
- Compatibility with multiple tasks

PanUrban Dataset

Statistics

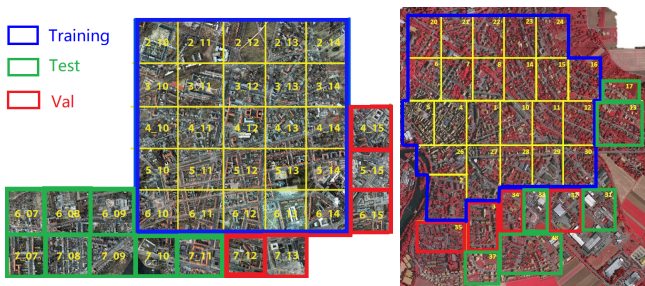
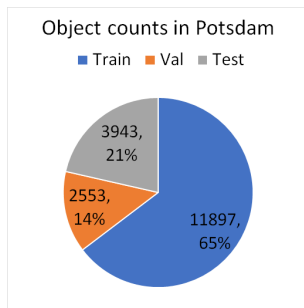
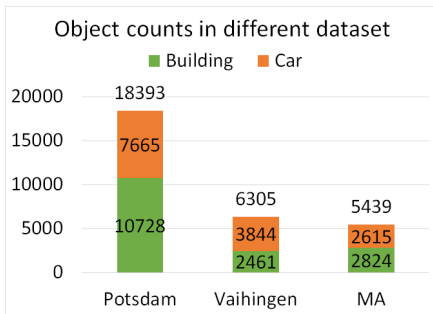


Figure: Dataset split in Potsdam and Vaihingen

- **Training** is a stitched patch.
- **Test** and **Val** are in small image patch.

PanUrban Dataset

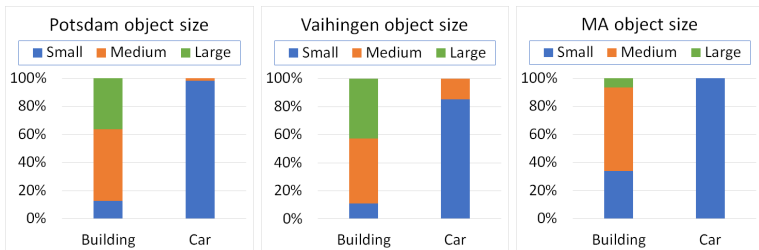
Statistics



- Number of objects in datasets: Potsdam > Vaihingen > MA
- Number of objects in Train/Val/Test subsets: Train(65%), Test(21%), Val(14%)

PanUrban Dataset

Statistics



Object size s in pixel:

small: $s \in [0, 32^2)$, medium: $s \in [32^2, 96^2)$, large: $s \in [96^2, \infty)$

- most of buildings belongs to medium and large object
- most of cars belongs to small object.

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Model Division

The model of panoptic segmentation can be divided into 6 parts listed as follows:

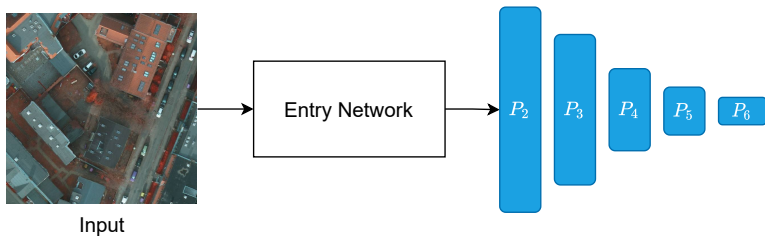
- **entry network**
- **region proposal network**
- **instance classification**
- **instance mask segmentation**
- **semantic segmentation**
- **fusion**

Loss functions:

$$\mathcal{L} = \mathcal{L}_{proposal} + \mathcal{L}_{instance} + \mathcal{L}_{semantic}$$

Entry Net

Entry Net Structure



- input: source image
- feature maps P_i with $i \in [2, 6]$ in different scale.

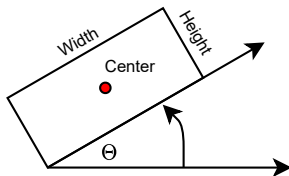
Region Candidates Proposal

Region Proposal Network(RPN)

What is a region? - a bounding box enclosed area.



ABB vs.RBB

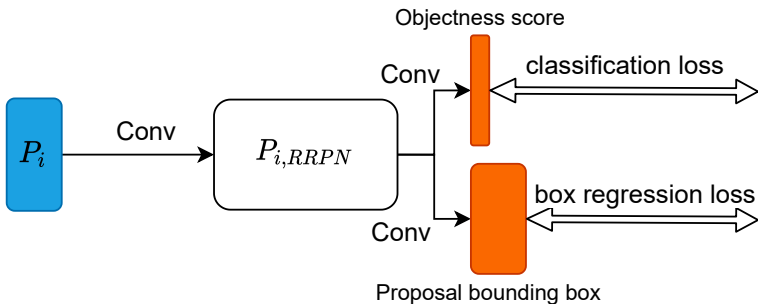


parameterization of RBB

- axis-aligned bounding box(ABB) vs. rotated bounding box(RBB)
- parameterization: (x_c, y_c, w, h) .vs. (x_c, y_c, w, h, θ)
- compact alignment with rotated bounding box.

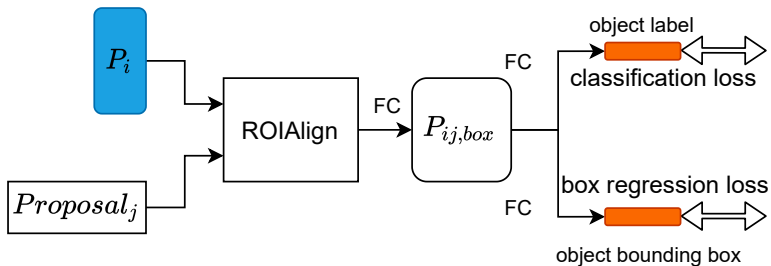
Region Candidates Proposal

Region Proposal Network(RPN) Structure



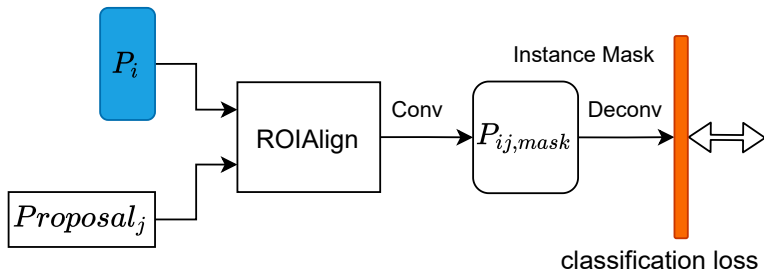
- Input: feature map from entry network P_i
- Output: objectness score & object bounds
- Loss: $\mathcal{L}_{proposal}^{cls}$ and $\mathcal{L}_{proposal}^{box}$

Object Classification



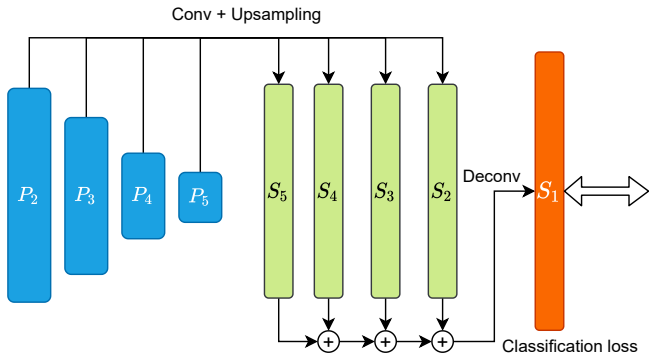
- Input: P_i , $Proposal_j$
- Output: classified object region
- Loss: $\mathcal{L}_{instance}^{box}$ and $\mathcal{L}_{instance}^{cls}$

Mask Segmentation



- Input: $P_i, Proposal_j$.
- Output: classified object region
- Loss: $\mathcal{L}_{instance}^{mask}$

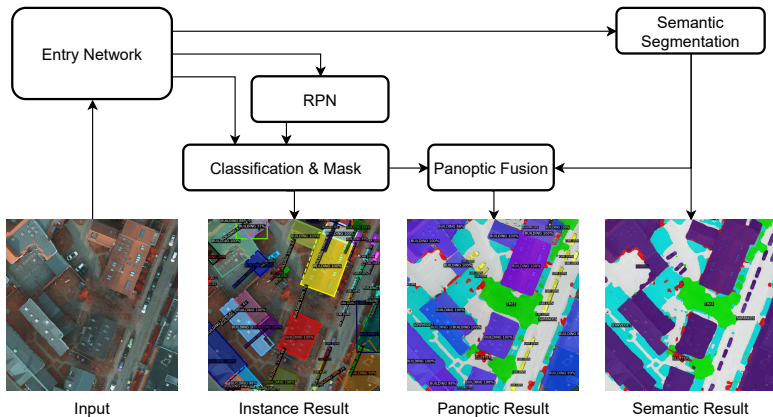
Semantic Segmentation



- input: Multi-scale feature map $P_2 - P_5$
- output: predicted semantic label
- loss: $\mathcal{L}_{semantic}$

Panoptic Segmentation

Full model



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Task Metrics

Panoptic Quality

$$\begin{aligned}
 PQ &= \frac{\sum_{p,q \in TP} \text{IoU}(p, q)}{|TP| + \frac{1}{2}|FP| + \frac{1}{2}|FN|} \\
 &= \underbrace{\frac{\sum_{p,q \in TP} \text{IoU}(p, q)}{|TP|}}_{\text{segmentation quality(SQ)}} \times \underbrace{\frac{|TP|}{|TP| + \frac{1}{2}|FP| + \frac{1}{2}|FN|}}_{\text{recongition quality(RQ)}}
 \end{aligned}$$

where:

p, q = prediction and groundtruth of matched **segments**.

TP = true positive segment, which has $\text{IoU}(p, q) > 0.5$

$|*|$ = count of **segments**, **not pixels**.

SQ = average IoU of **matched segments**

RQ = F1 score of segments.

Experimental Setting

Content of experiment:

- 1 influence of pretraining on semantic branch.
- 2 performance comparison on ABB and RBB.
- 3 inference cross different datasets.

Additional experiment can be found in the thesis:

- 1 full range augmentation performance.
- 2 pretraining on RPN.
- 3 ablation study.
- 4 parameter study.

Pretraining on Semantic Branch

Pretrained weight is applied on the entry net.

Pretraining \ IoU	mIoU	IoU _{clutter}	IoU _{l.veg}	IoU _{imp.surf.}	IoU _{thing}	IoU _{tree}
COCO _{weight}	60.2	8.9	68.1	77.2	82.9	63.8
ImageNet _{weight}	60.1	13.6	68.6	75.9	79.9	62.5
None	50.6	4.8	56.6	67.4	62.5	61.5
COCO _{full weight}	64.1	22.3	69.4	78.6	84.1	66.0

Table: Semantic Metrics w.r.t Pretraining: mIoU denotes averaged Intersection over Union over all classes, subscript hints class name

Result from Semantic Branch:

- Comparison on *COCO_{weight}* vs. *ImageNet_{weight}* and None Pretraining.
- Comparison on semantic categories.
- Comparison with fully trained model, inferring the influence of instance branch.

Full range augmentation

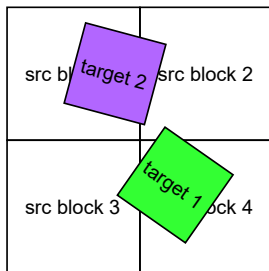


Figure: Example of Full range augmentation on source block 1-4

Features:

- random location
- random orientation
- random small scale difference.
- extract features across source blocks.

ABB vs. RBB

Comparison on bounding box format

Metrics	All classes			Things			Stuff		
	PQ _{all}	SQ _{all}	RQ _{all}	PQ _{th}	SQ _{th}	RQ _{th}	PQ _{st}	SQ _{st}	RQ _{st}
Potsdam _R	54.4	74.2	72.7	70.0	83.3	84.2	46.6	69.6	67.0
Potsdam _A	53.9	74.1	72.1	69.4	84.2	82.8	46.2	69.1	66.8
Vaihingen _R	53.6	63.2	71.0	63.9	82.5	77.8	48.5	53.6	67.6
Vaihingen _A	53.8	63.7	70.8	64.7	82.8	78.6	48.4	54.1	67.0

Table: PQ,RQ,SQ in axis-aligned box(ABB) and rotated bounding box(RBB) in dataset Potsdam and Vaihingen, with full range augmentation

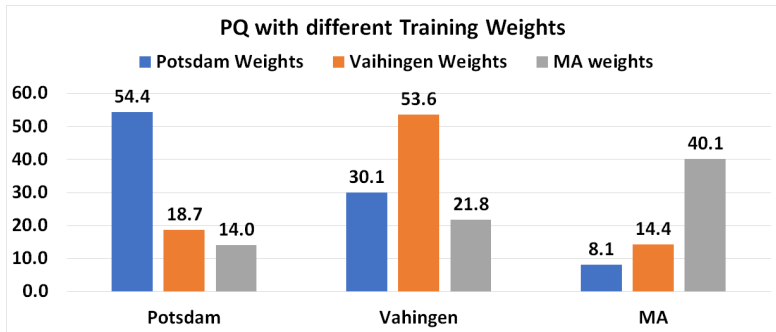
- Comparison on Box formats: subscript H and R.
- Comparison on things and stuff.

Metrics	PQ _{all}	SQ _{all}	RQ _{all}	PQ _{th}	SQ _{th}	RQ _{th}	PQ _{st}	SQ _{st}	RQ _{st}
MA _R	40.1	58.1	56.9	47.1	74.4	62.7	36.6	49.9	54.0
MA _A	31.5	54.0	48.4	38.3	73.8	51.5	28.1	44.2	46.9

Table: PQ,RQ,SQ on axis-aligned box and rotated box in dataset MA, with rotational augmentation

Cross Dataset Performance

This experiment applies training on a dataset and inference on other datasets.



- Model tend to overfit the training data.

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Conclusions and Outlook

Conclusions:

- PanUrban dataset is developed with a semi-automatic workflow, which can be applied in multiple aerial image tasks.
- Training a panoptic segmentation model has achieved a plausible result which can be set as a baseline in future development.

Future work:

- Limited generalization ability requires techniques to limit overfitting on training data, applying different normalization layers or add regularization terms.

References I



Ross Girshick. “Fast r-cnn”. In: *Proceedings of the IEEE international conference on computer vision*. 2015, pp. 1440–1448.



Kaiming He et al. “Mask r-cnn”. In: *Proceedings of the IEEE international conference on computer vision*. 2017, pp. 2961–2969.



Alexander Kirillov et al. “Panoptic feature pyramid networks”. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019, pp. 6399–6408.



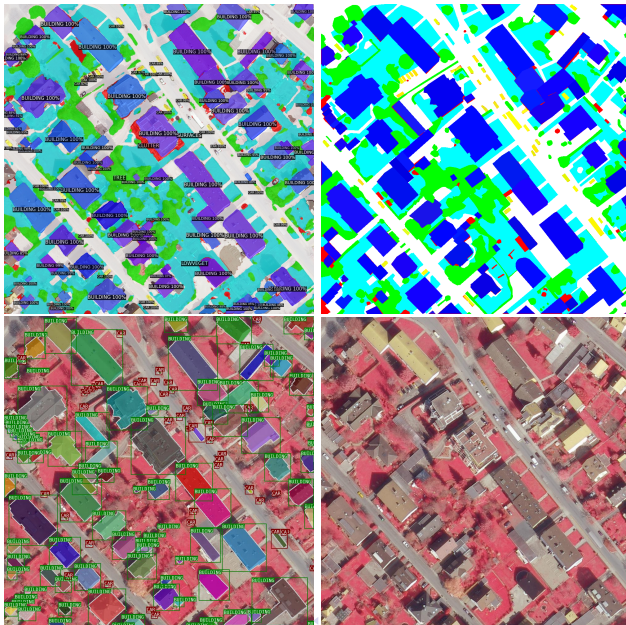
Alexander Kirillov et al. “Panoptic segmentation”. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019, pp. 9404–9413.

References II



Shaoqing Ren et al. “Faster r-cnn: Towards real-time object detection with region proposal networks”. In: *arXiv preprint arXiv:1506.01497* (2015).

Prediction Samples - MA



Prediction Samples - Potsdam

