

Real Time Domain Adaptation in Semantic Segmentation

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AML

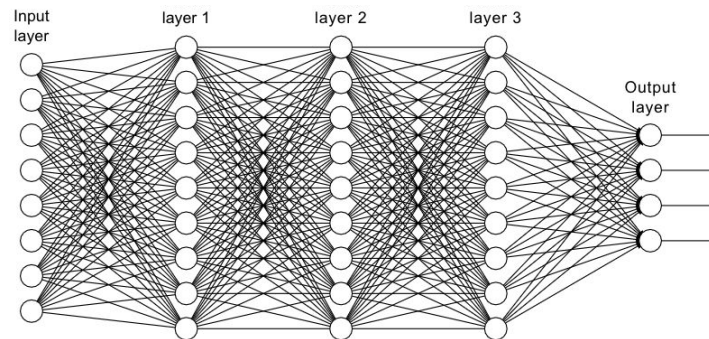
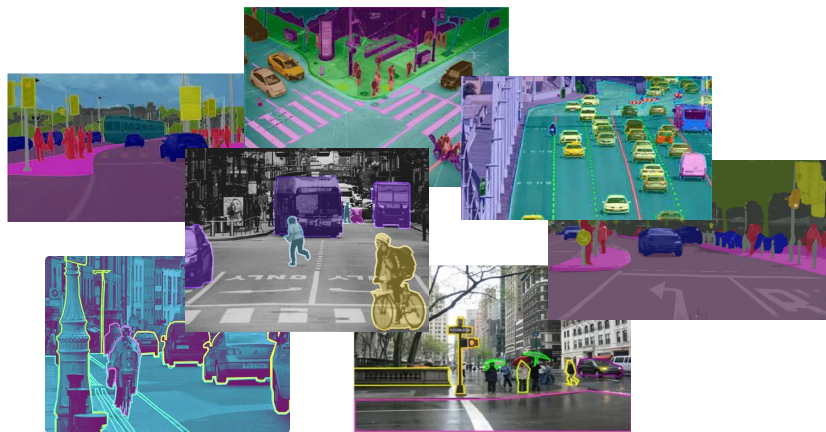
Semantic Segmentation

- Task of assigning a category label to each pixel of an image.
- Multiple applications: e.g. self-driving cars, land-cover mapping...



Challenges

- Collect pixel-wise annotations is extremely expensive in terms of time.
- Performance at the expense of efficiency.





Performance and efficiency

- Performance at the expense of efficiency (in terms of parameters, latency and hardware requirements)
 - Large number of parameters
 - High latency
 - Deployments issues on practical scenarios



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→ Solution: use **REAL TIME SEGMENTATION NETWORK**

→ Trade-off between efficiency and complexity



Burden of Labeling

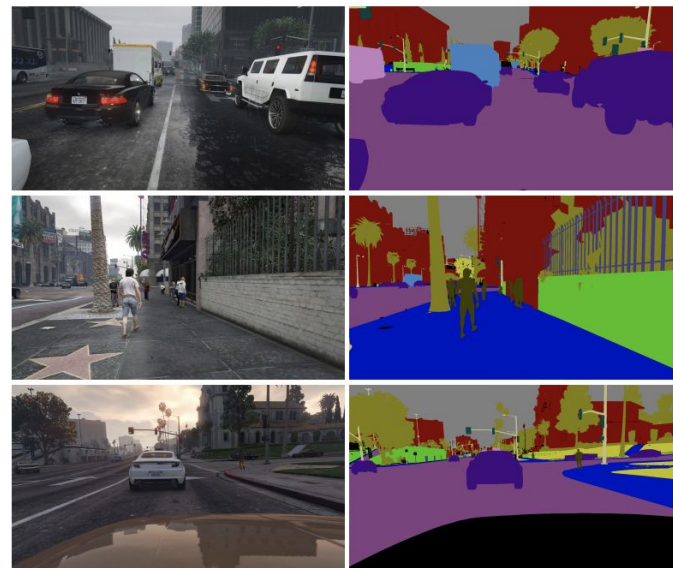
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→ Solution 1: use **SYNTHETIC DATASETS**

- Generated by a software
- Close to real images
- Pixel-wise accurate ground truth
- Cheaper
- E.g. images from GTA5 videogame



[1] "The cityscapes dataset for semantic urban scene understanding.", Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele.



Burden of Labeling

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→ Solution 2: reuse **data from another annotated domain**.

- No synthetic-to-real shift



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→ Problem: gap between domains

DOMAIN ADAPTATION!

LoveDA

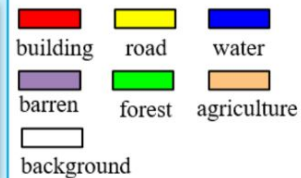
- High spatial resolution (HSR) land-cover mapping.
- The LoveDA dataset contains 5987 HSR images with 166768 annotated objects from three different cities.



urban



rural

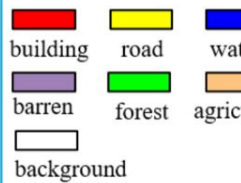
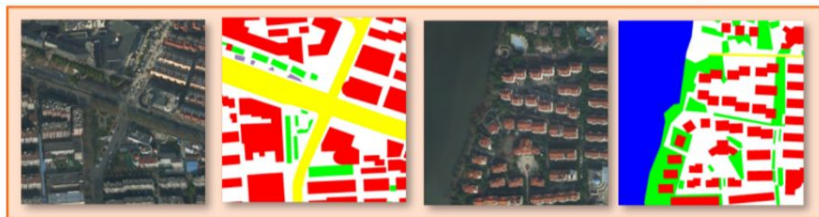


LoveDA

- High spatial resolution (HSR) land-cover mapping.
- The LoveDA dataset contains 5987 HSR images with 166768 annotated objects from three different cities.

CHALLENGES:

1. multi-scale objects;
2. complex background samples;
3. inconsistent class distributions.





Your project

3 STEPS:

1. BASELINES

- Train the network on Urban scenario, with multiple networks under different constraints (frame per seconds, GFLOPs, parameters...)
- Test your trained network on the Rural scenario.
- Implement some *data augmentation* techniques to improve performance.

2. DOMAIN ADAPTATION

3. EXTENSIONS

- E.g. Implement solutions to address the problem of class imbalance in the dataset.
- E.g. Perform pseudolabelling in the target domain
- ... is up to you! Propose you extension

THANK YOU!

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