Lab Course Cognitive Systems: Depth & Bounding Box Prediction

Interim Presentation

WS 17/18

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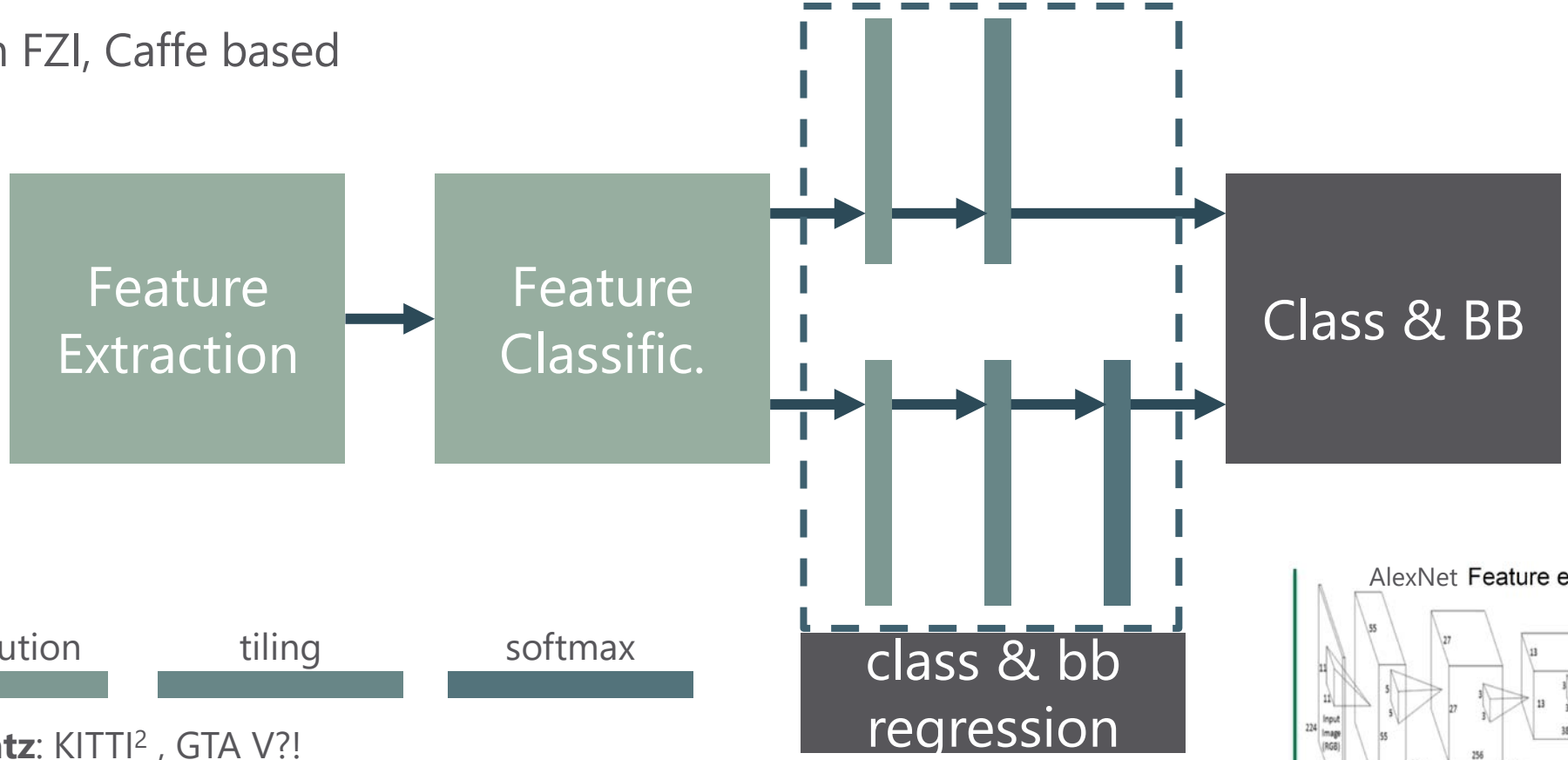
Problem Definition

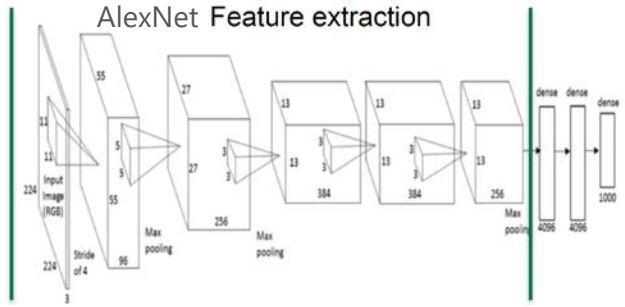
- Vehicle detection with CNN
- Issues: poor performance for largely overlapping vehicles
- Possible solution: using depth information

1. Concept

Learning from depth images for monocular object detection with convolutional neural networks, MA A. Lesi

- DeepTLR[1] based object detection - class and bounding box regression
- From FZI, Caffe based





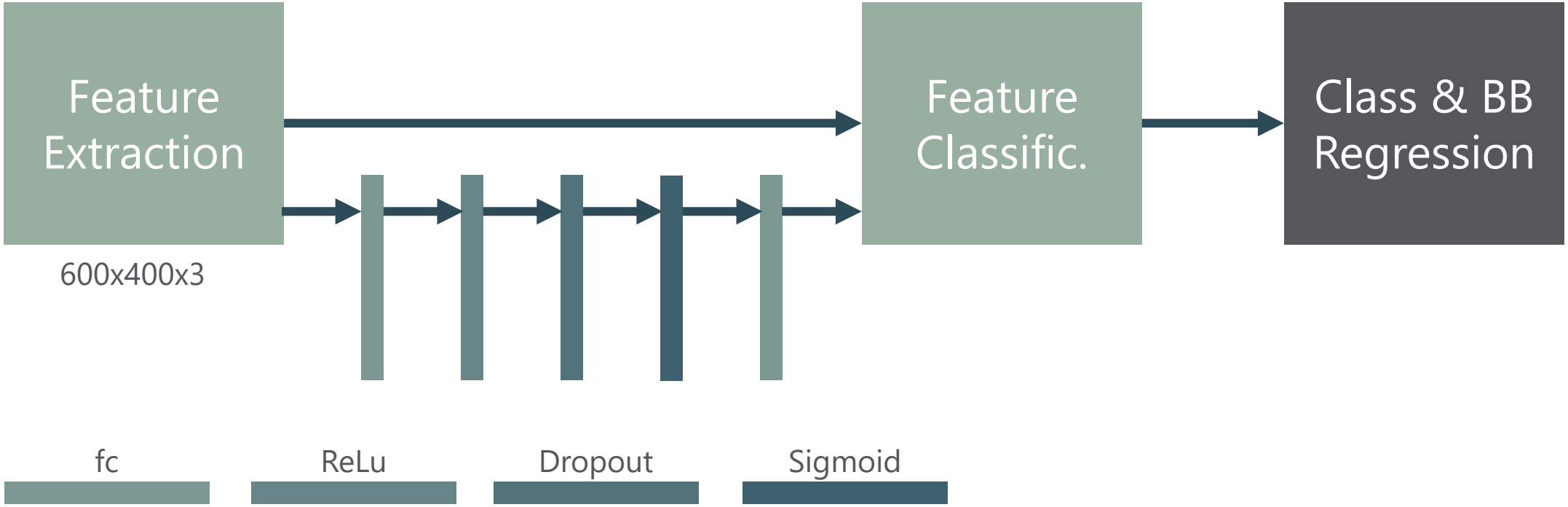
Datensatz: KITTI[2] , GTA V?!

[1]http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7535408
[2]http://www.cvlibs.net/publications/Geiger2012CVPR.pdf

1. Concept

Learning from depth images for monocular object detection with convolutional neural networks, MA A. Lesi

- Joint convolution depth prediction and object detection
- Against using of superpixels



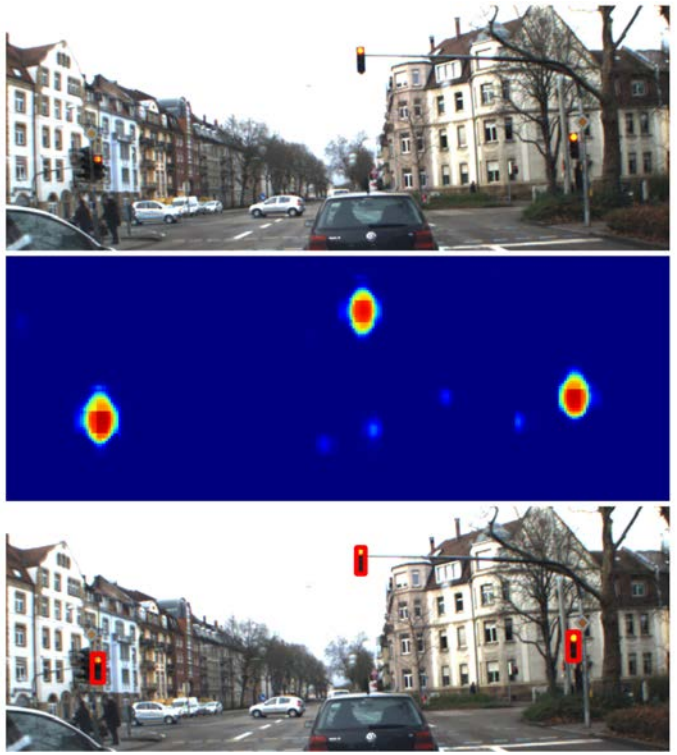
1. Concept

Learning from depth images for monocular object detection with convolutional neural networks, MA A. Lesi

- Current State:
  - ✓ Caffe running
  - ✓ Data processing & augmentation
  - ✓ LMDB creation
  - ✗ First training on KITTI
  - ✓ Evaluation routines

  - → Using code from M. Weber and A. Lesi
  - → No modifications on framework planned
  - → Inference Speed: 20 – 45 ms

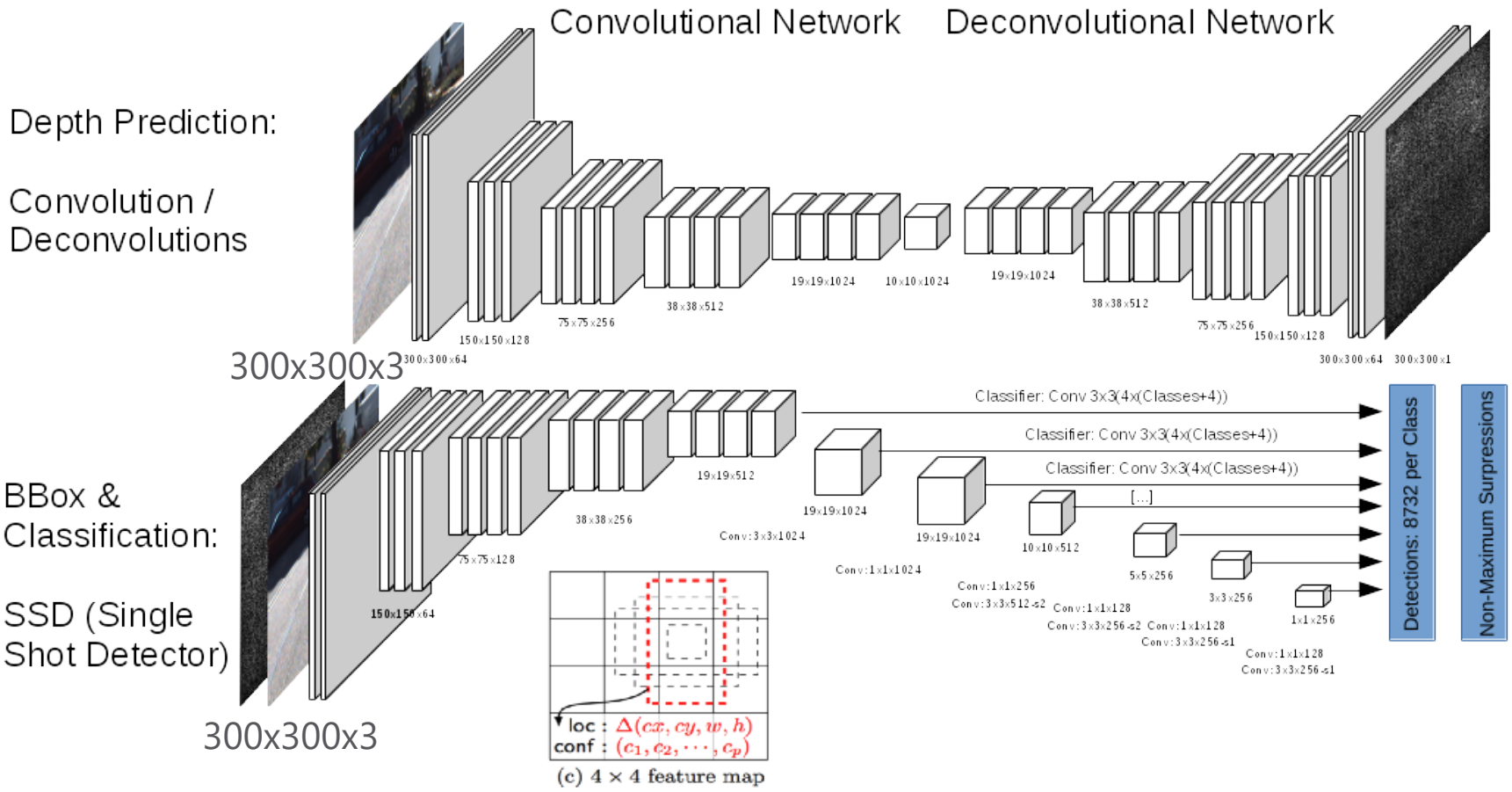
Caffe



2. Concept

Deeper Depth Prediction with Fully Convolutional Residual Networks, Laina et al.
+ SSD: Single Shot MultiBox Detector, Liu et al.

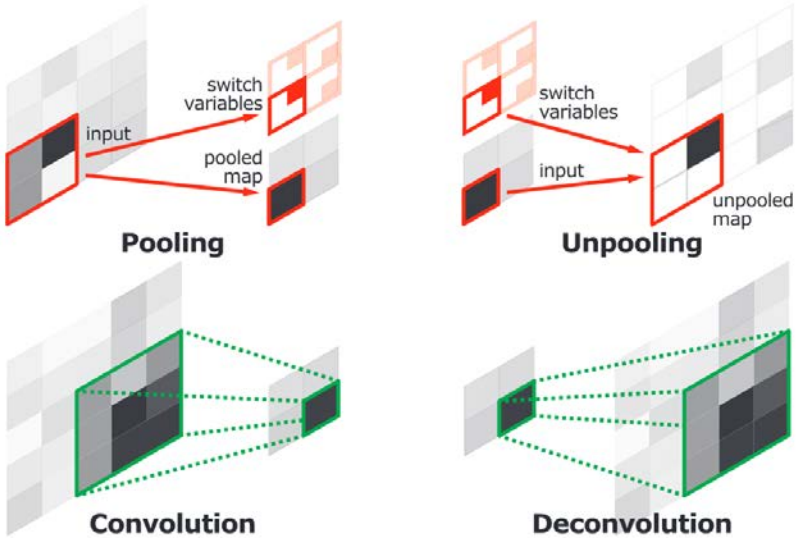
- 2 Stages: DeconvNet with ResNet50 layers for depth prediction + SSD detector

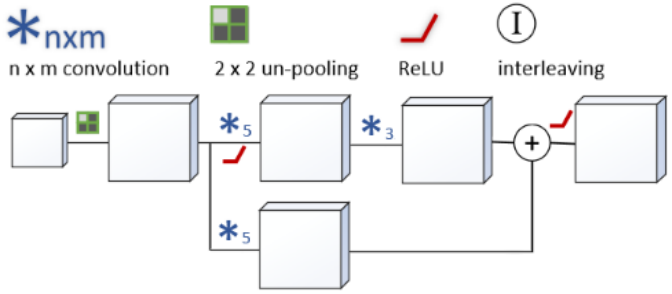


2. Concept

Deeper Depth Prediction with Fully Convolutional Residual Networks, Laina et al.
\+ SSD: Single Shot MultiBox Detector, Liu et al.

- Using pooling and unpooling layers





Pooling: is designed to filter noisy activations in a lower layer by abstracting activations in a receptive field with a single representative value

→ spatial information within a receptive field is lost during pooling, which may be critical for precise localization

Unpooling: performs the reverse operation of pooling and reconstruct the original size of activations

→ increases the spatial resolution of feature maps

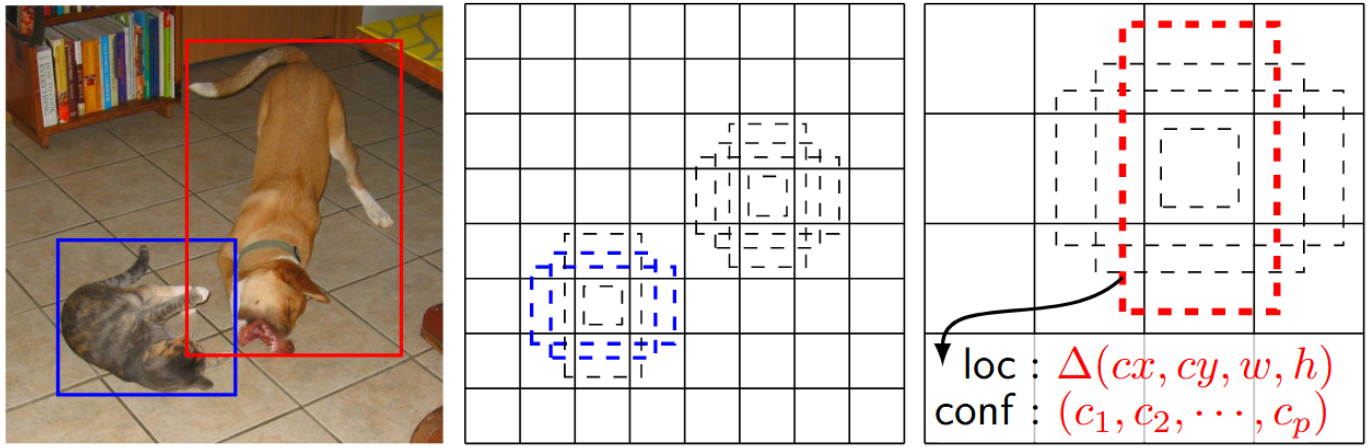
Up-projection: adds 3×3 convolution after the unpooling and a projection (=res-blocks) connection from the lower resolution feature map to the result

→ allows high-level information to be more efficiently passed forward in the network while progressively increasing feature map sizes

2. Concept

Deeper Depth Prediction with Fully Convolutional Residual Networks, Laina et al.
\+ SSD: Single Shot MultiBox Detector, Liu et al.

- Object detection based on VGG
- Uses predefined anchor boxes with different sizes and ratios
- For every box will be calculated if object is in box or near at it, the object class and the bb



→ Unused boxes will be deleted and non-maximum suppression is used to obtain final boxes

→ Faster than YOLO!

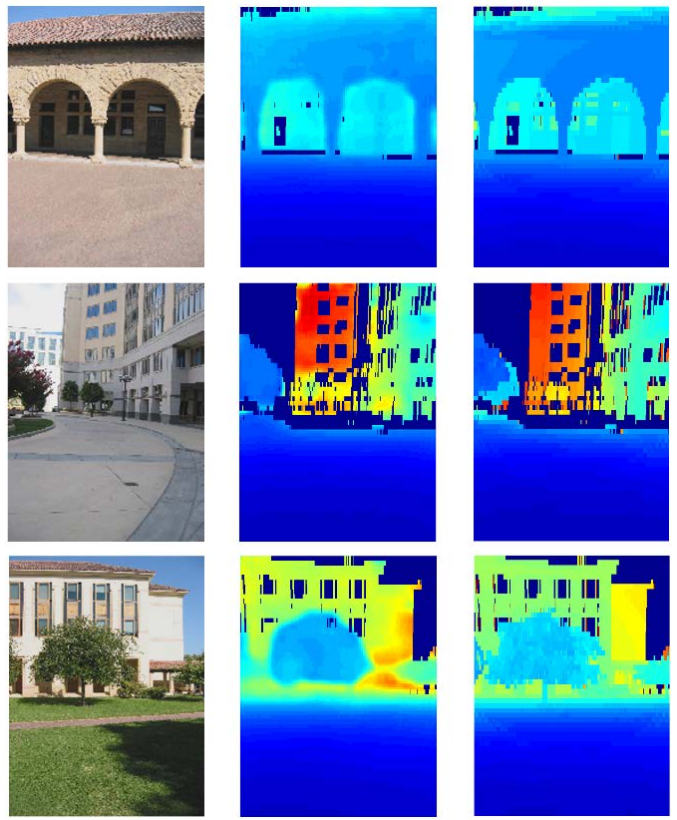
2. Concept

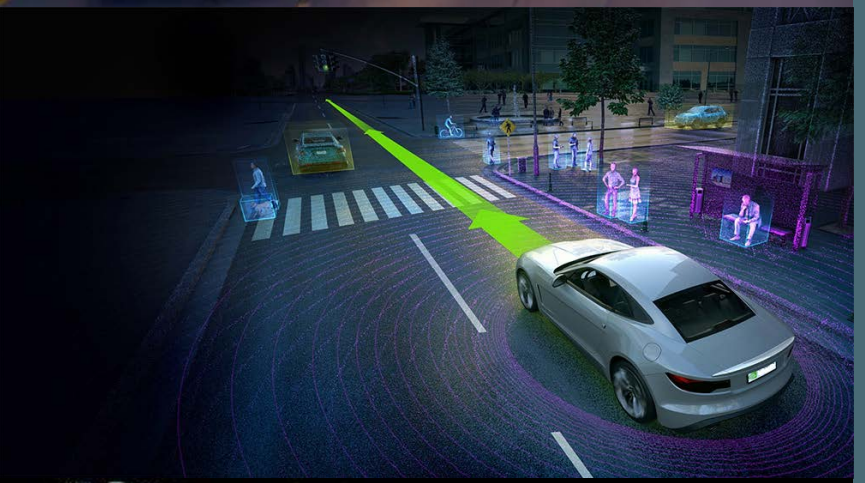
Deeper Depth Prediction with Fully Convolutional Residual Networks, Laina et al.
+ SSD: Single Shot MultiBox Detector, Liu et al.

- Current State:
  - ✓ Up and running isolated frameworks
  - ✗ When and where combine outputs – inputs?!
  - ✓ Data processing & augmentation
  - ✗ First training on KITTI
  - ✓✗ Evaluation routines

  - → Both networks use VGG for feature extraction
  - → Both are implemented in Tensorflow 🤩
  - → Inference Speed:

    DeconvNet: ~200 ms on CPU, SSD: ~22 ms on Titan X





Questions?