Complex YOLO with Uncertainty

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Introduction

- Object detection and classification has been a field of great interest especially in autonomous vehicles
  - YOLO predicts bounding boxes and class probabilities in 2D (Redmon et al., 2016)
  - Complex YOLO takes YOLO to 3D by adding an E-RPN network (Simon et al., 2018)
- We would like the model to output uncertainty about its own predictions. This allows the human to further confirm the decisions that the model makes with high uncertainty.

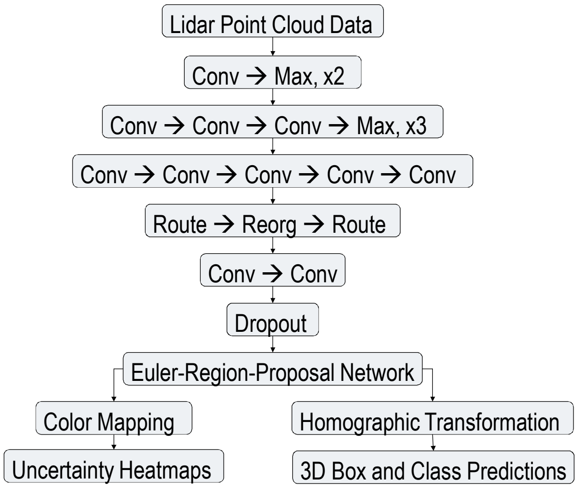
Problem Formulation

(1) Given a point-cloud image, draw 3D box around detected objects and classify them
- Achieved results comparable to Complex YOLO.

(2) Use Bernoulli dropout to gauge uncertainty about the locations and sizes of bounding boxes:
- Visualized this uncertainty using heat maps.

(3) Added additional loss targeting overlapping boxes:
- Limited effect…

Methods



Lidar Point Cloud Data

Conv → Max, x2

Conv → Conv → Conv → Max, x3

Conv → Conv → Conv → Conv → Conv

Route → Reorg → Route

Conv → Conv

Dropout

Euler-Region-Proposal Network

Color Mapping → Uncertainty Heatmaps

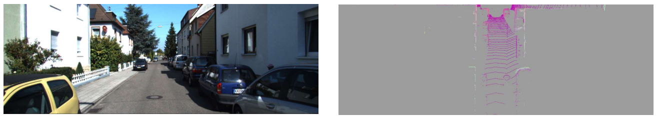
Homographic Transformation → 3D Box and Class Predictions

$$\text{IOU} = \frac{\text{Area}(C \cap D)}{\text{Area}(C \cup D)}$$

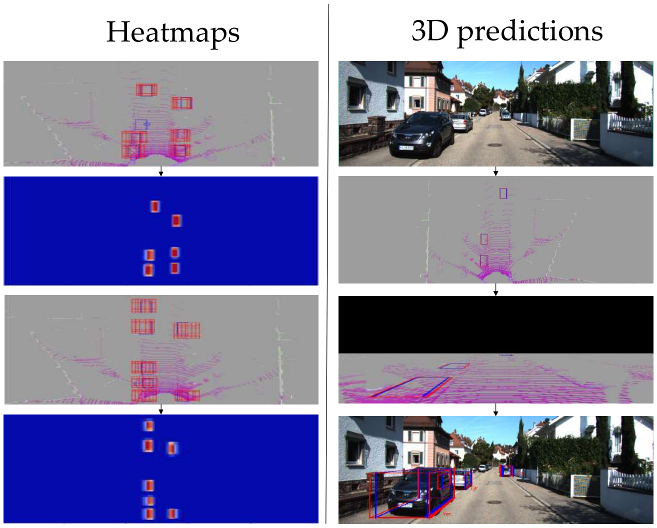
$$L_{total} = L_{YOLO} + L_{Euler}$$

Data

- Velodyne point clouds (29 GB)
- Left color images of object dataset (12 GB)
- Camera calibration matrices of point clouds (16 MB)
- Training labels of object dataset (5 MB)



Results



Heatmaps

3D predictions

Model	Class	Distribution	AP
Complex Yolo	Car	> 75%	85.89%
Uncertainty Yolo	Car	> 80%	80.01%
Uncertainty Yolo	Van	< 10%	27.58%

Conclusions and Future Study

Contributions
- Effectively incorporated uncertainty into 3D object detection while preserving average precision.
- Projected predictions to 3D using homography.
- Attempted to improve models on overlapping predictions.

Future Work
- Train model directly on labeled 3D data to make direct predictions without having to use homography and visualize uncertainty in 3D.

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