Using LiDAR for Enhanced Perception

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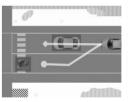


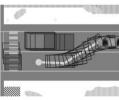
Perception

- One of the four cornerstones
- Heavily relied upon by decision and planning systems









Sensing

Physics-based models of camera, LIDAR, RADAR, GPS, etc.

Perception

Programs for object detection, lane tracking, scene understanding, etc.

Decisions and planning

Programs and multiagent models of pedestrians, cars, etc.

Control

Dynamical models of engine, powertrain, steering, tires, etc.

Sense

camera, LIDAR, GPS, computer vision, machine learning, neural networks, data

Decide and Control

navigation, path planning, physics, code

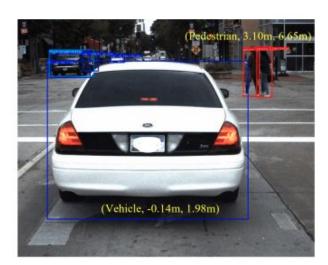
Act

computers, networks, engine, steering, brake



Perception on GEM

- Only uses camera
- Assumes width of pedestrian (0.47m) when calculating distance
- Processes objects from a few classes
 - Pedestrians, vehicles, traffic signs, etc.

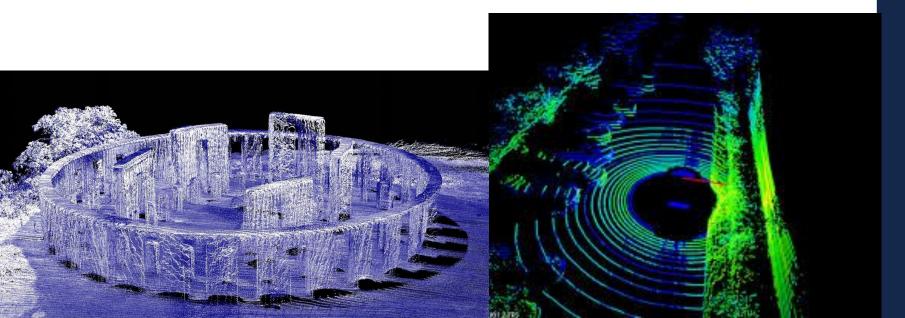






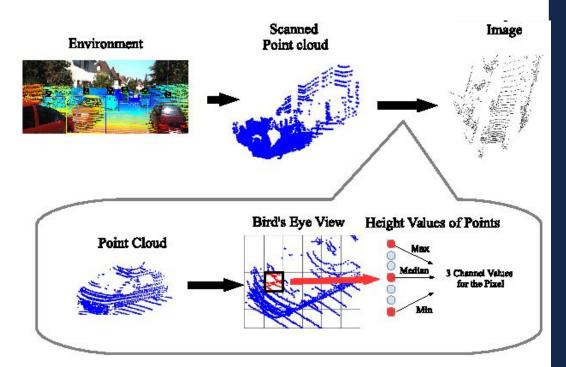
Why use LiDAR?

- Cameras are heavily constrained by lighting
- Distance measurement built into the sensing
- Can detect neighboring objects that the camera isn't trained to detect
 - Strangely-shaped vehicles, barriers, etc.



Our Goal

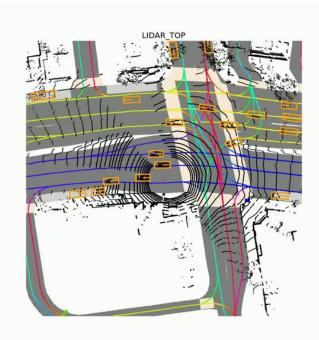
- Detect neighboring objects using LiDAR
 - Speed estimation
- Don't be limited to specific objects
- Reasonable computation time
 - Laptop GPU
 - 30 FPS





What We Used

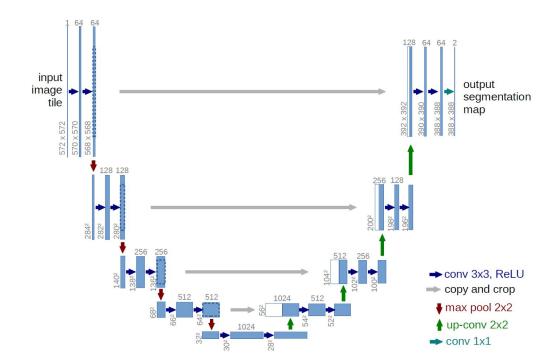
- U-Net
 - Fully Convolutional Network for biomedical image segmentation
- Lyft Level 5 Dataset
 - 50,000+ annotated frames
 - LiDAR, Camera





U-Net

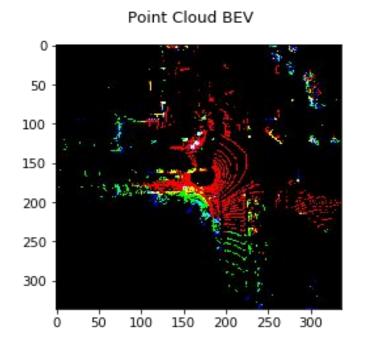
- Semantic segmentation
- Image -> Segmentation Map
- "What" and "Where"



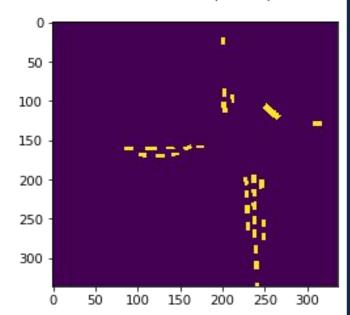


Pre Processing

- Bird's eye view
 - Centered around vehicle
- Ground truth
 - Draw boxes







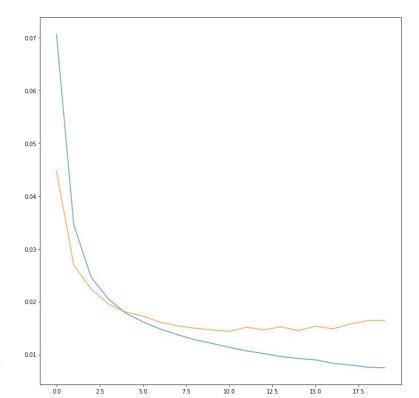
Implementation

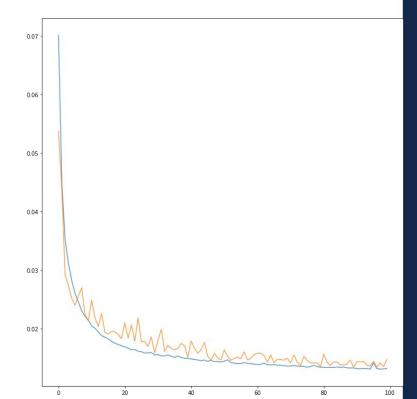
- 80/20 Train Validation Split
- U-Net (modified)
 - Slightly less deep
- Training
 - Adam for optimization
 - Cross Entropy Loss
 - Overfitting



Dealing with overfitting

- Training loss: Blue
- Validation loss: Orange
- Added Dropout Layers

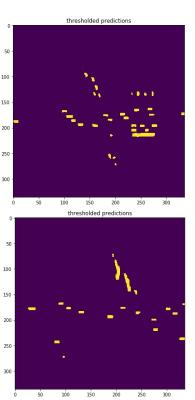


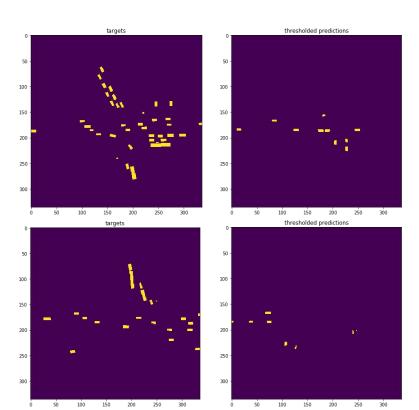


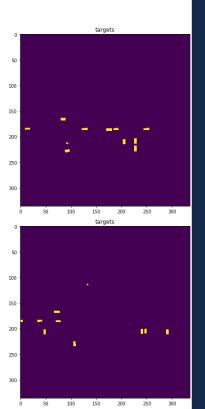


Results

Threshold probability -> binary image

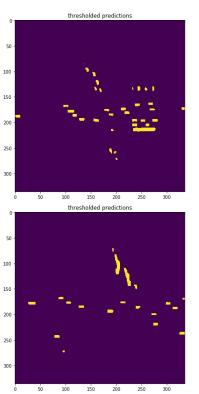


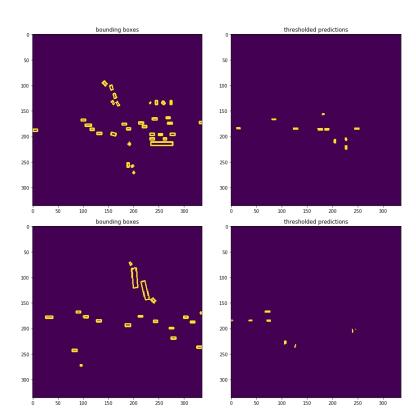


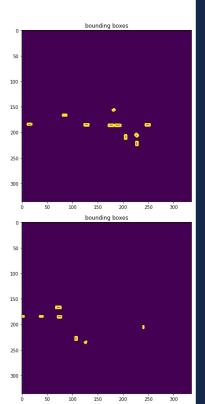


Post Processing

- Binary image -> List of rectangles
 - Find contours
 - Contours -> (rotated) bounding rectangle







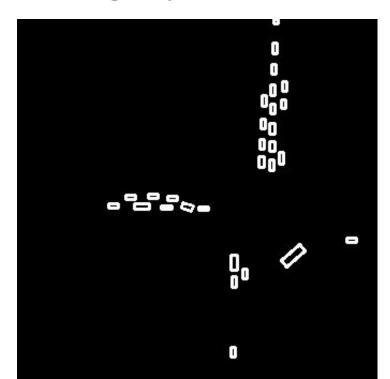
Speed Estimation

- Track relative speeds of nearby objects
- Accurately predict collisions
- Safe lane-switching



Speed Estimation Algorithm

- Identify objects over consecutive frames
- Store changes in position
- Summarize average speed





Lack of Ground Truth

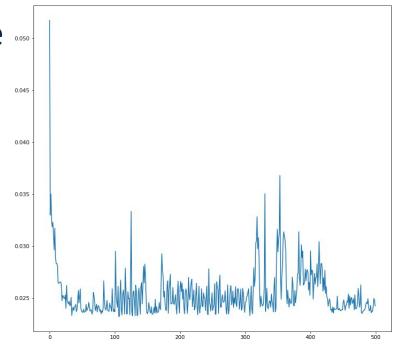
- Currently impossible to test algorithm accuracy
- Can run a test with cars whose exact speeds are known



Cost

- 0.026 seconds per frame for inference
 - 38 FPS
- GTX 1050 Ti
 - 4 GB Memory
- No additional hardware

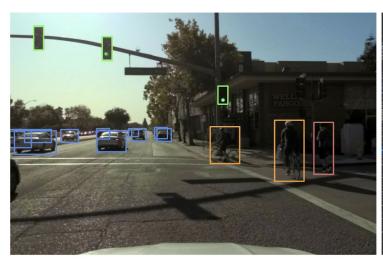
Inference time (in seconds)





Future Work

- Fuse with other sensors
 - · Camera, Radar
- Collision Prediction







Potential Downsides

- Neural Nets are a "black box"
 - Verification
 - Adversarial attacks
- LiDARs are expensive
- Distinguishing between objects



Sources

- 1. U-Net: Convolutional Networks for Biomedical Image Segmentation
 - a. https://arxiv.org/abs/1505.04597
- 2. Online monitoring for safe pedestrian-vehicle interactions
 - a. https://arxiv.org/abs/1910.05599
- 3. Lyft Dataset: https://www.lyft.com/level5/data
- 4. PyTorch: https://pytorch.org/
- 5. OpenCV: https://opencv.org/





Questions?

 Thanks to Prof Mitra and Prof Kim along with Ted and Yangge for this awesome class!





Project Contributions

- Adit
 - Training + Tuning Model
 - Speed detection
- Eric
 - Training + Tuning Model
 - Data Preprocessing/Postprocessing

