KITTI-360: A Novel Dataset and Benchmarks for Semantic Scene Understanding in 2D and 3D

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ellis
European Laboratory for Learning and Intelligent Systems

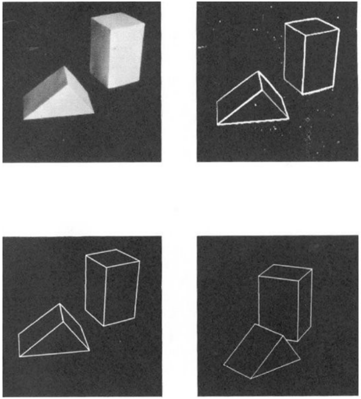
Combining Perception and Action

Darpa Robotics Challenge, 2013

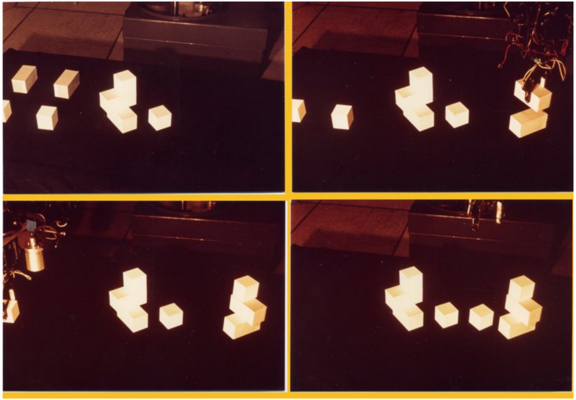
AlphaZero, 2017

- Robots work well in **simulation** but not yet in the **real world**

Combining Perception and Action



Larry Roberts, 1963

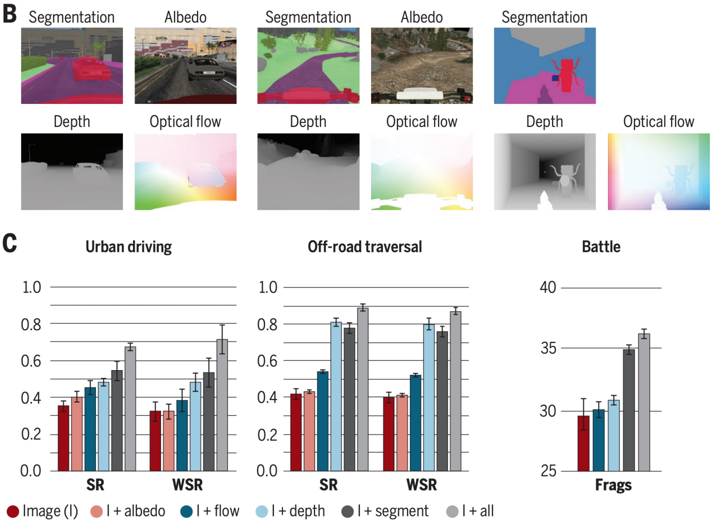


MIT Copy Demo, 1970

- Early **vision** driven by **robotics** but developed into its own field

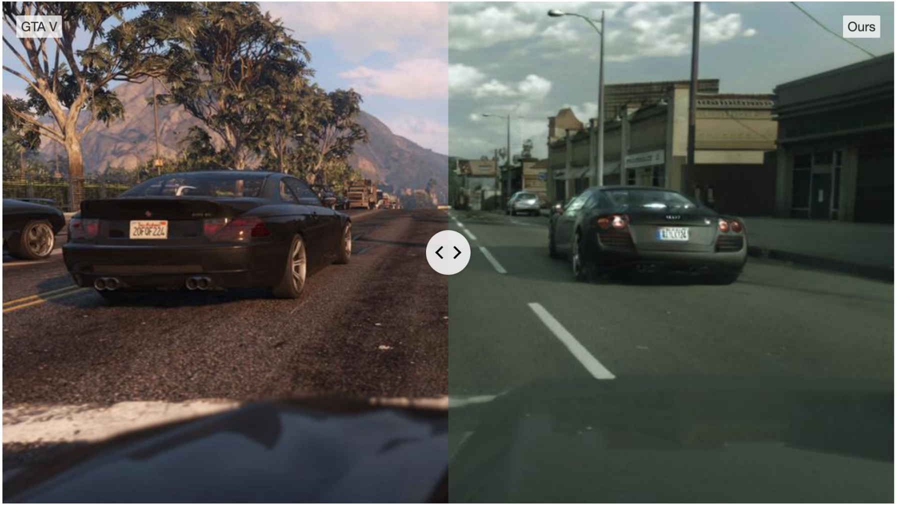
Roberts: Machine perception of three-dimensional solids. PhD Thesis, 1963.

Combining Perception and Action



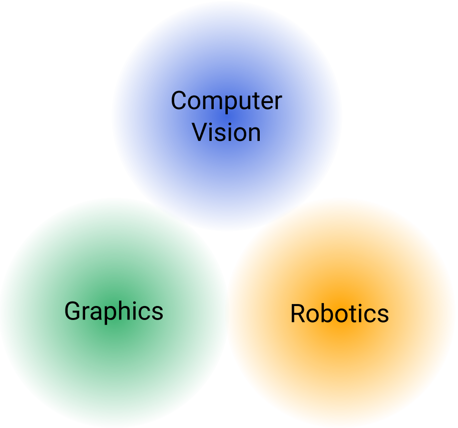
Zhou, Krähenbühl, Koltun: Does Computer Vision Matter for Action? Science Robotics, 2019.

Combining Perception and Simulation



Richter, AlHaija, Koltun: Enhancing Photorealism Enhancement. Arxiv, 2021.

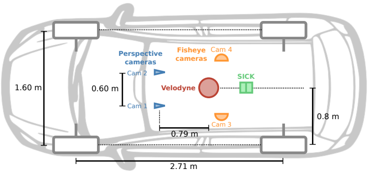
Towards Full Autonomy

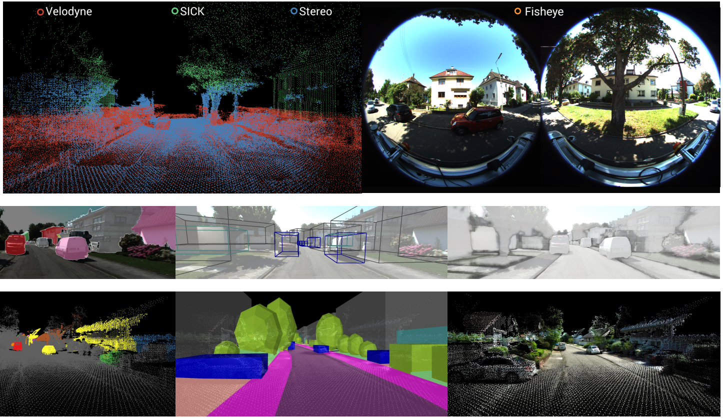


Full autonomy requires a **concerted effort** across different fields

Which datasets and benchmarks do we need?

KITTI-360





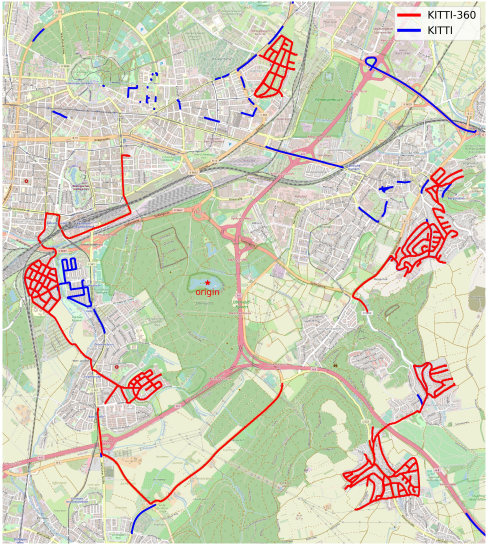
- Rich 360° sensory information
- Accurate global localization
- Semantic instance labels in 2D & 3D
- New challenging benchmarks

Liao, Xie and Geiger: KITTI-360: A Novel Dataset and Benchmarks for Urban Scene Understanding in 2D and 3D.

Data Collection

Data:

- **73.7** km, **4** $\times$ **83,000** frames
- **Georegistered** poses $\Rightarrow$ OpenStreetMap
- Minimal trajectory overlap with KITTI



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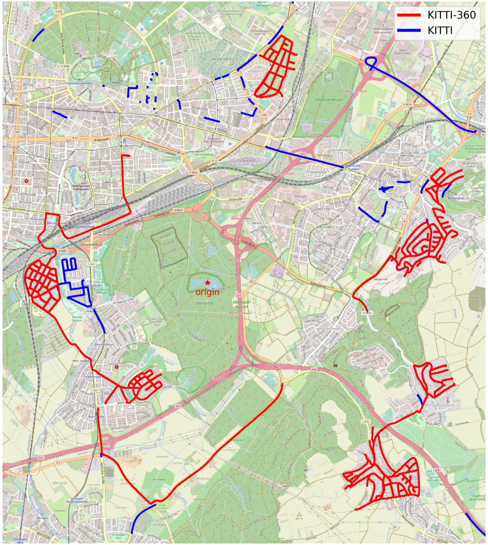
Sensors:

- 2 × perspective cameras
- 2 × **fisheye cameras** ⇒ 360° Imagery



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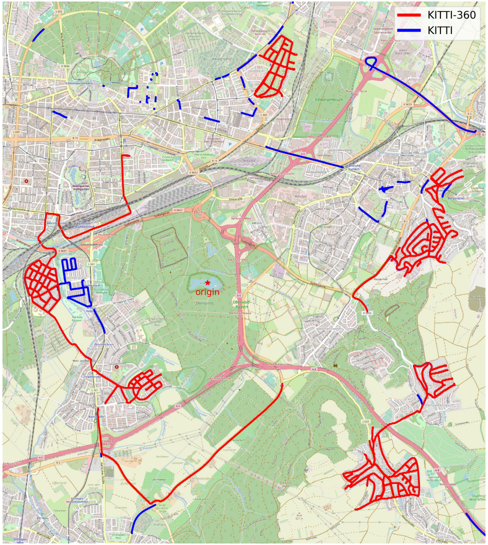
- Velodyne HDL 64 LiDAR
- **SICK pushbroom LiDAR**



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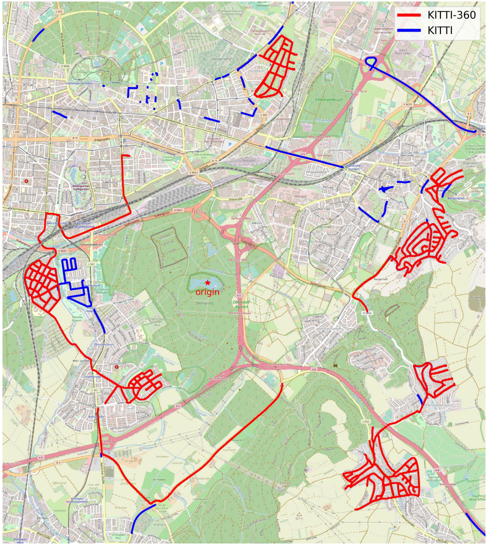
- IMU/GPS measurement unit



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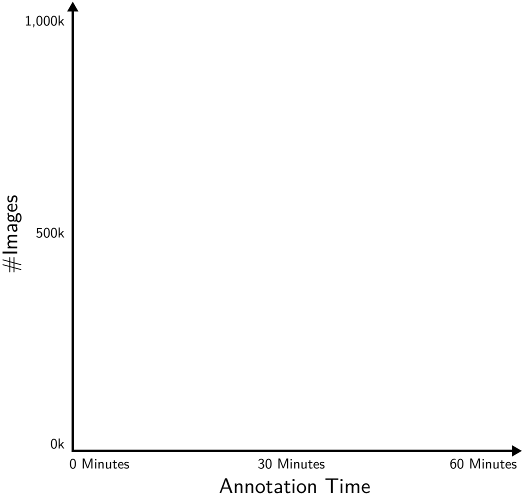
How can we annotate semantics at large scale?

The Curse of Dataset Annotation



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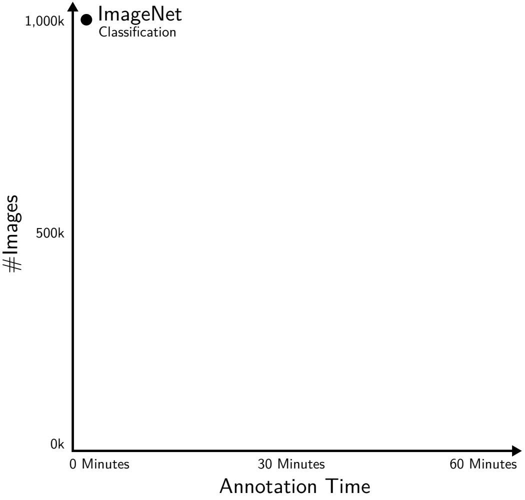

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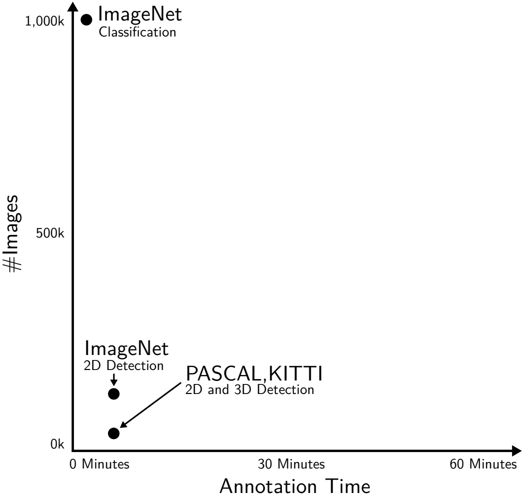

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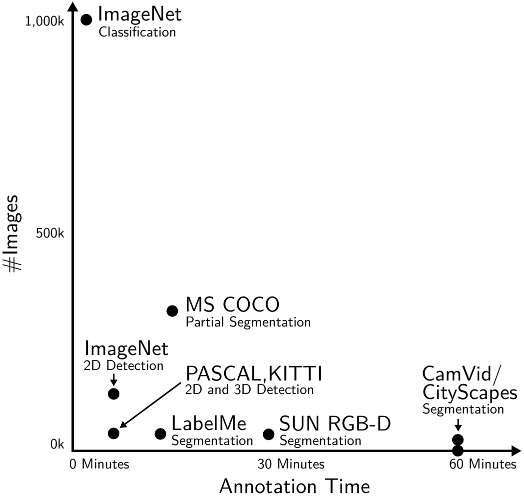

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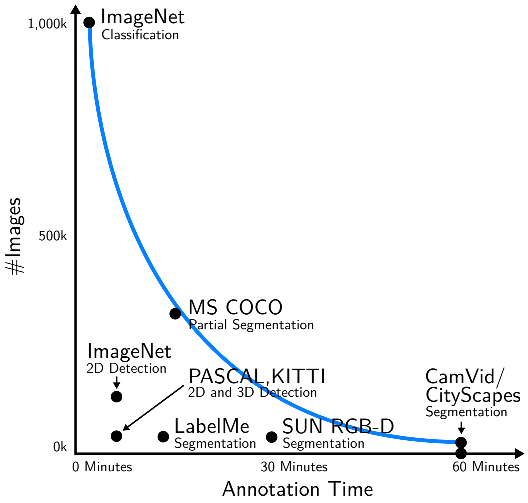

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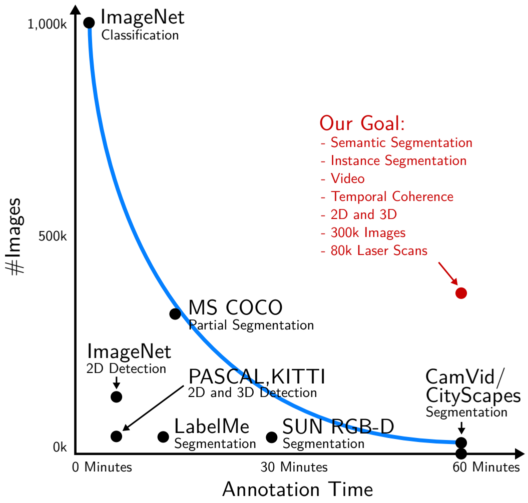
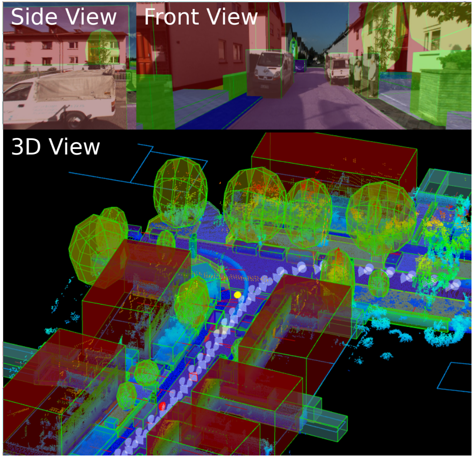


3D to 2D Semantic and Instance Label Transfer



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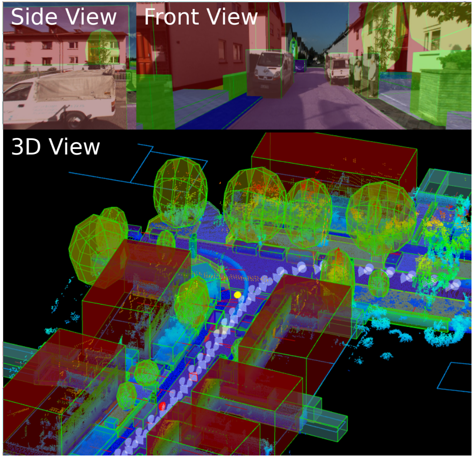

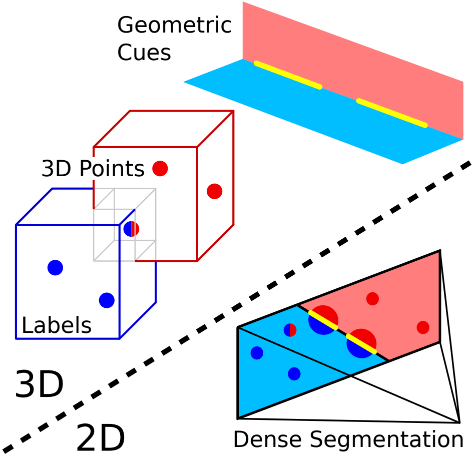

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- Object instances can be more easily separated in 3D

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Challenges:

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- 3D annotations are coarse and imprecise
- Dynamic objects are challenging to annotate

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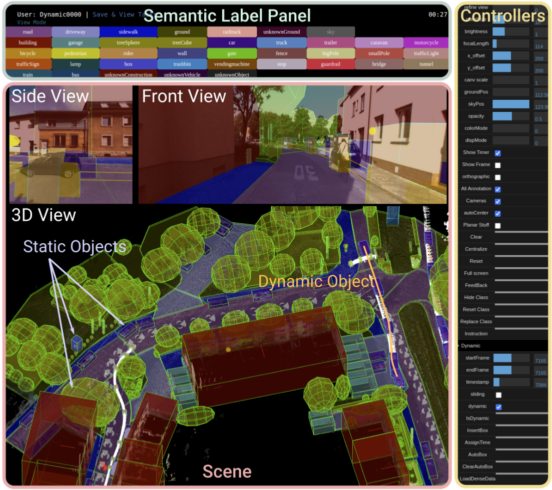
Data Annotation

Annotation Tool

- 3D Annotation
- 2D Camera Views
- Supports annotation of static and dynamic objects
- Fast annotation functions



Data Annotation

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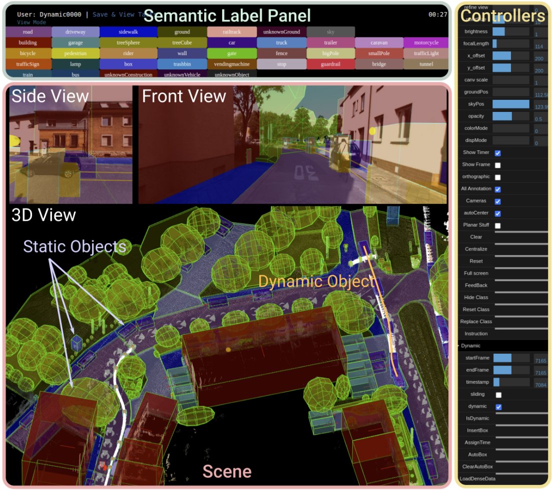
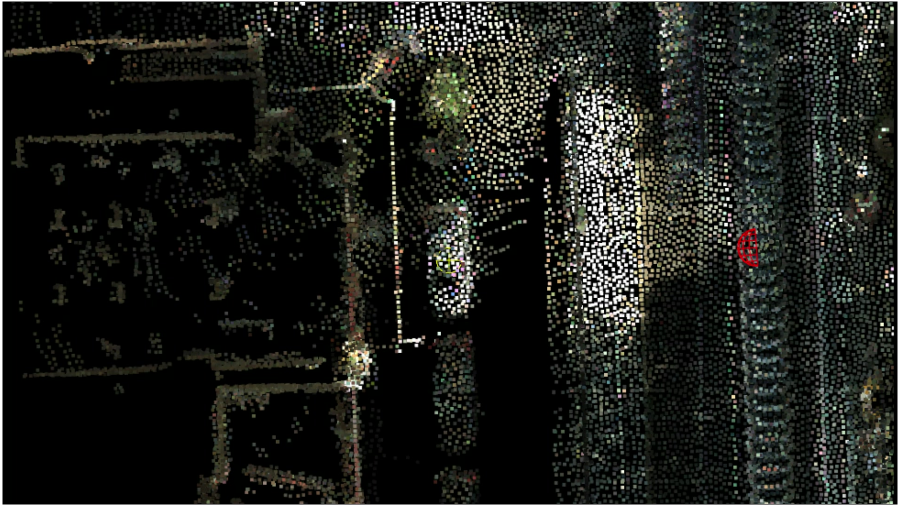
Annotation Time:

- 3D $\Rightarrow$ 1 min per image
- 2D $\Rightarrow$ 90 min per image



Static Object Annotation



Semi-Automatic Dynamic Object Annotation

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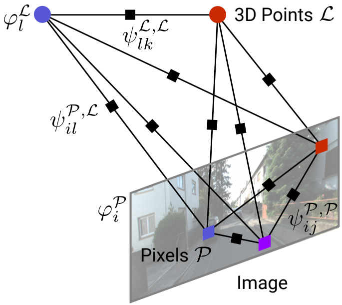
3D-to-2D Label Transfer



Variables:

- 3D Points: $\{s_i | i \in \mathcal{L}\}$
- Pixels: $\{s_i | i \in \mathcal{P}\}$

Conditional Random Fields:

$$E(\mathbf{s}) = \sum_{i \in \mathcal{P}} \varphi_i^{\mathcal{P}}(s_i) + \sum_{l \in \mathcal{L}} \varphi_l^{\mathcal{L}}(s_l) + \sum_{i,j \in \mathcal{P}} \psi_{ij}^{\mathcal{P},\mathcal{P}}(s_i, s_j) + \sum_{l,k \in \mathcal{L}} \psi_{lk}^{\mathcal{L},\mathcal{L}}(s_l, s_k) + \sum_{i \in \mathcal{P}, l \in \mathcal{L}} \psi_{il}^{\mathcal{P},\mathcal{L}}(s_i, s_l)$$

3D-to-2D Label Transfer

Inference:

- Factorized mean field $Q(\mathbf{s}) = \prod_{i \in \mathcal{P} \cup \mathcal{L}} Q_i(s_i)$
- Efficient variational inference [Krähenbühl & Koltun, CVPR 2011]
- Confidence map obtained via entropy over marginal distribution

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Learning:

- Empirical risk minimization
- Stochastic gradient descent
- Same loss for instance & semantic segmentation

Qualitative Comparison to Baselines

2D Label Propagation [Vijayanarasimhan et al., 2012]

Qualitative Comparison to Baselines

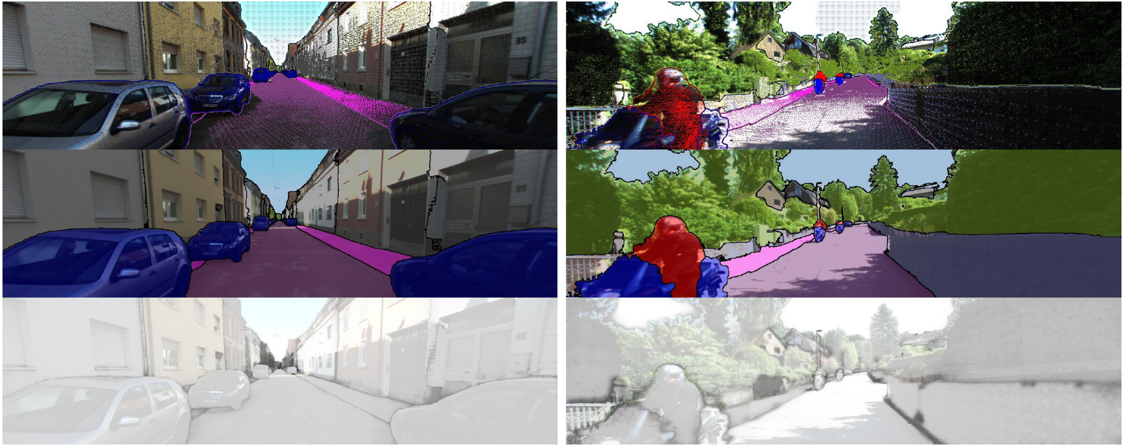
Proposed Method

Quantitative Results

Method	JI	Acc
LA	82.1	90.0
LA+PW	84.4	91.4
LA+PW+CO+3D	88.2	93.7
Full Model	89.0	94.1
Full Model (90%)	94.9	97.4
Full Model (80%)	96.6	98.2
Full Model (70%)	**97.5**	**98.7**

- LA: Local Appearance
- PW: 2D Pairwise Potentials
- CO: 3D Primitive Constraints
- 3D: 3D Point Constraints

Qualitative Results



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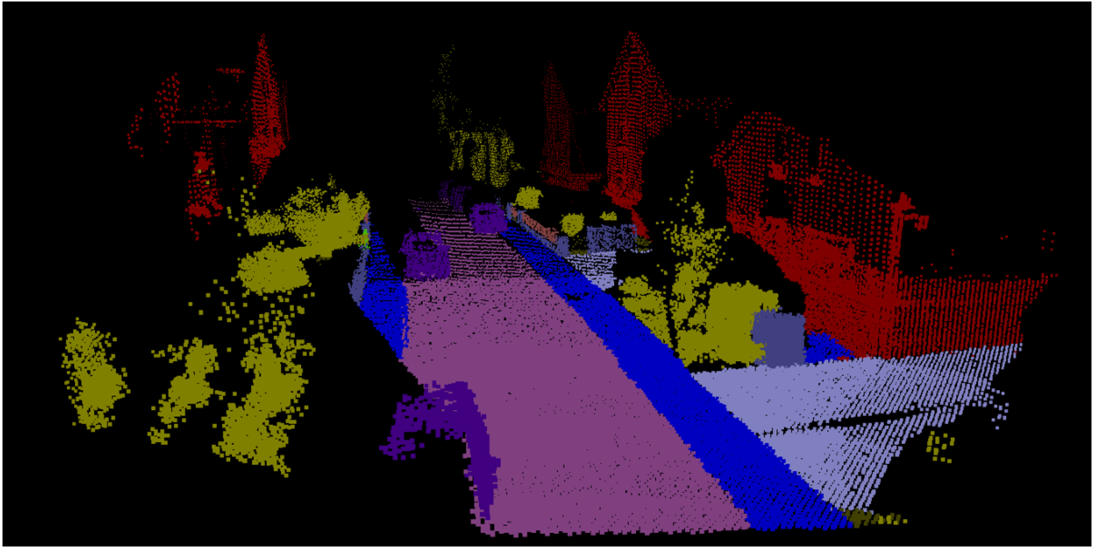

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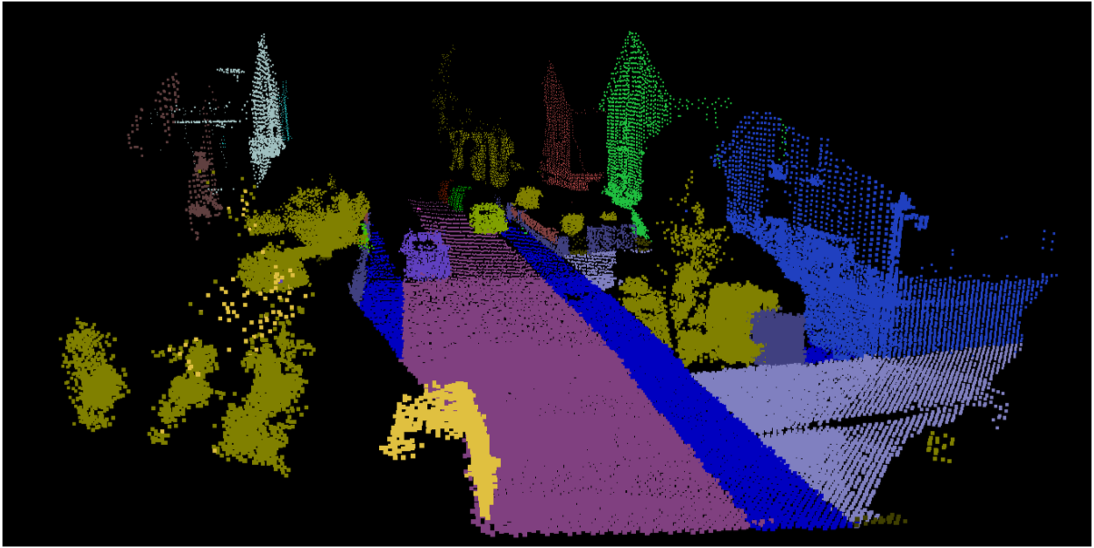

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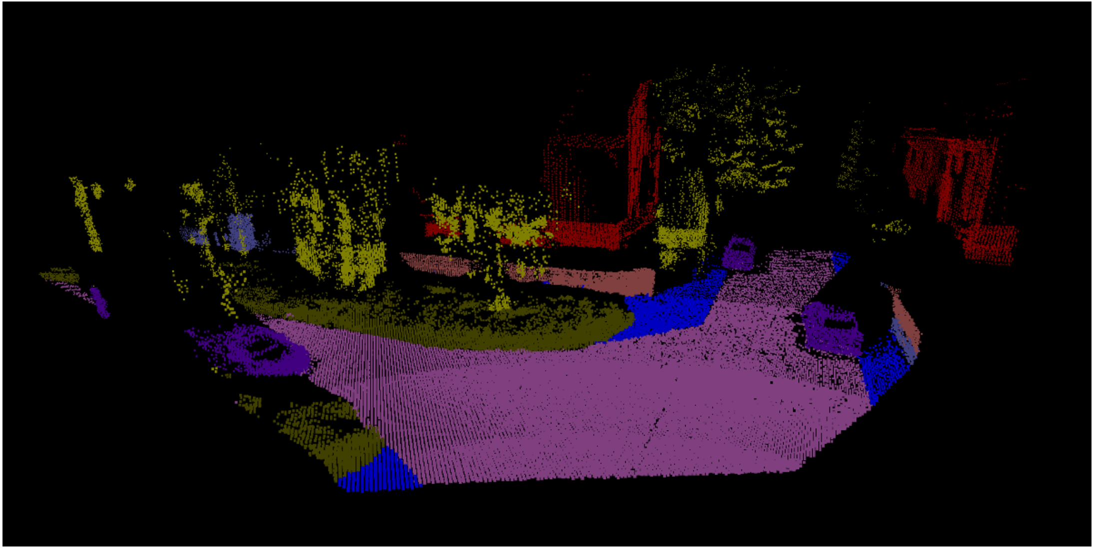

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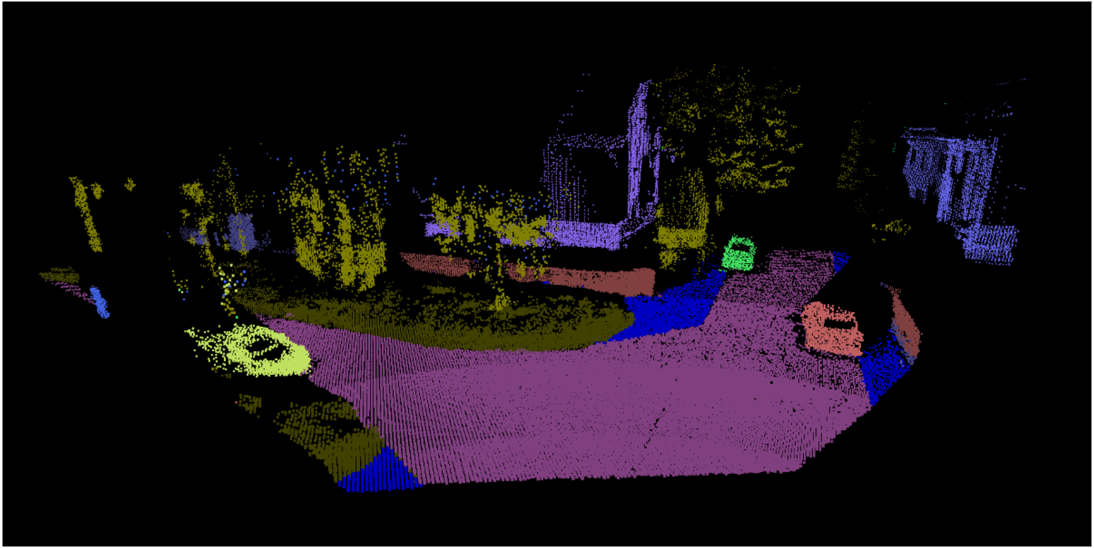

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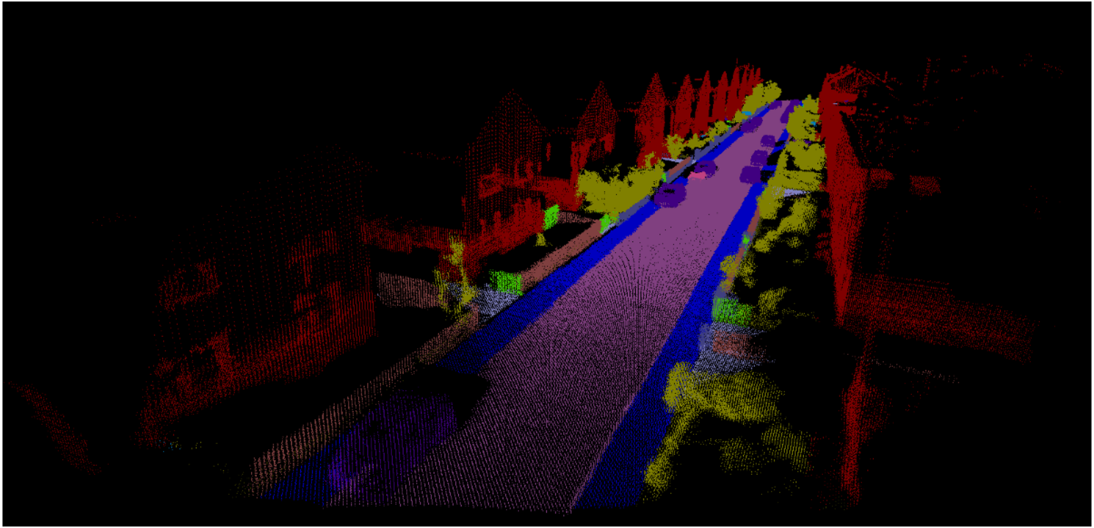

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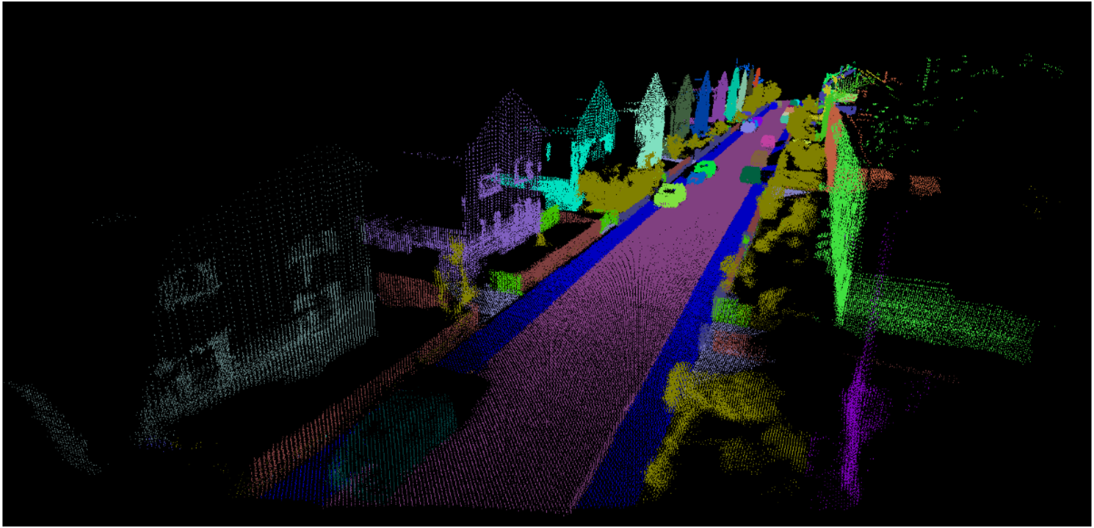
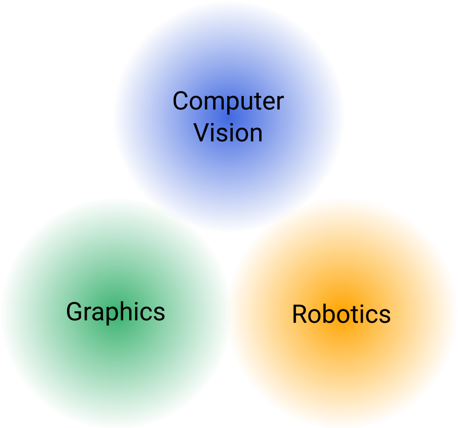


How can KITTI-360 help autonomous driving?

Benchmarks



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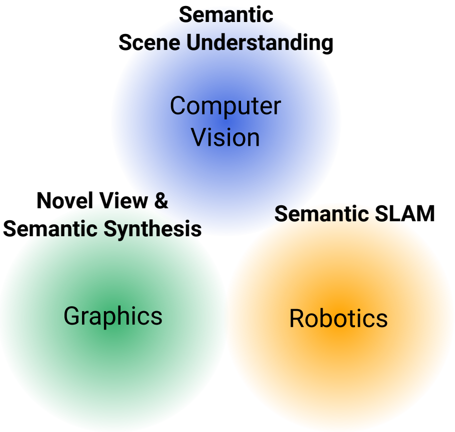
Benchmarks

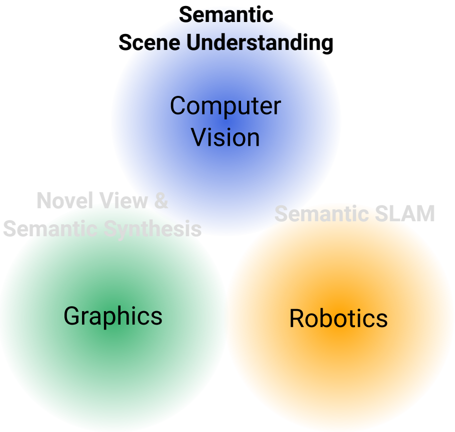

3D
Control
Localization
Detection
Sensing
Evaluation


Semantic
Scene Understanding
Computer
Vision
Novel View &
Semantic Synthesis
Semantic SLAM
Graphics
Robotics

Benchmarks

Semantic Scene Understanding

- 2D & 3D Semantic/Instance Segmentation
- 3D Bounding Box Detection
- Semantic Scene Completion



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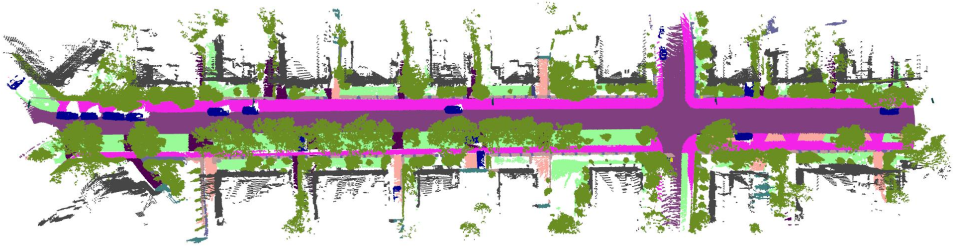
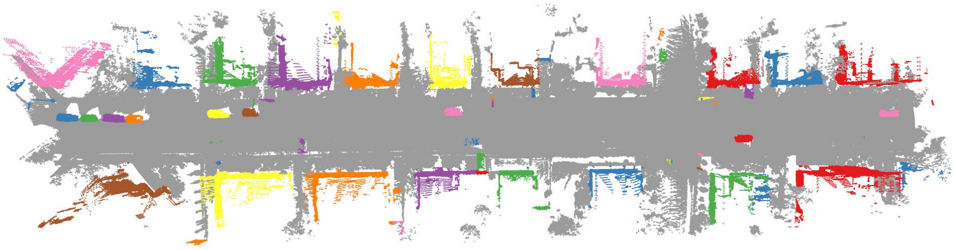
Semantic Scene Understanding



Semantic Segmentation & Completion

Semantic Scene Understanding



Instance Segmentation

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Semantic Scene Understanding

3D Bounding Box Detection

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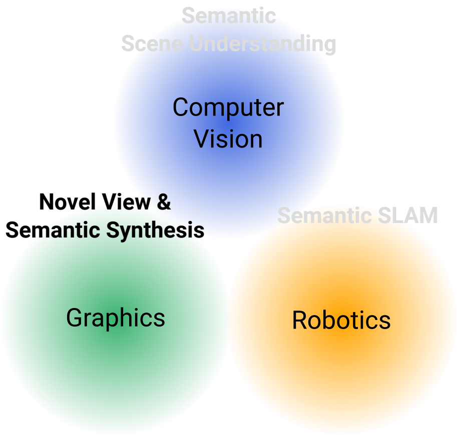
Benchmarks

Novel View Synthesis

- Appearance Synthesis
- Semantic Synthesis



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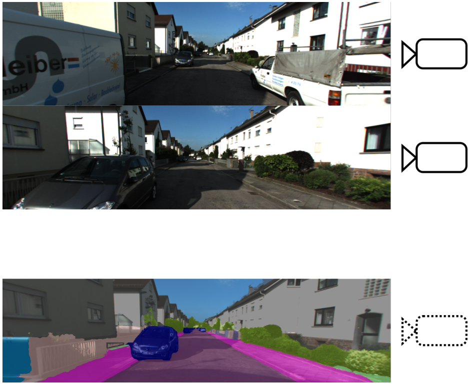
Novel View Synthesis

Task:

- Input: Perspective/fisheye image, poses, 3D point cloud (optional)
- Output: RGB Image / semantic map at novel viewpoints



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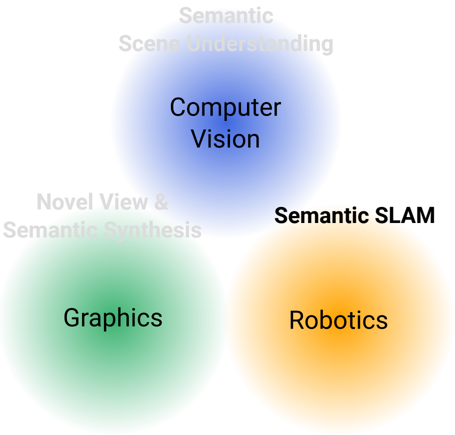
Benchmarks

Semantic SLAM

- Localization
- Geometric & Semantic Mapping



Semantic SLAM

Task:

- Input: Perspective images / LiDAR scans
- Output: Vehicle trajectory, scene geometry and semantics (=semantic mapping)

Evaluation:

- Mapping performance evaluated in local windows to eliminate effect of pose drift

Leaderboard

KITTI-360 Overview Demo Documentation Download Leaderboard Team Submit

Semantic SLAM

Trajectory Estimation

We adopt the standard Absolute Pose Error (APE) and Relative Pose Error (RPE) as metrics for evaluating pose estimation. We align the predicted trajectory to the ground truth using a rigid transformation to evaluate the APE. The RPE is evaluated between two frames with a distance of 1 meter.

- **APE:** Absolute Pose Error
- **RPE:** Relative Pose Error

	Method	Setting	Code	APE	RPE	Runtime	Environment	Compare
1	ORB-SLAM2			**1.91**	**2.02 %**		NVIDIA V100	☐
R. Mur-Artal and J. Tard'{o}s: ORB-SLAM2: An Open-Source SLAM System for Monocular, Stereo, and RGB-D Cameras. TRO 2017.								
2	SUMA++			3.13	2.71 %		NVIDIA V100	☐
X. Chen, A. Milioto, E. Palazzolo, P. Gigu\`{e}re, J. Behley and C. Stachniss: SuMa++: Efficient LiDAR-based Semantic SLAM. IROS 2019.								

Resources

KITTI-360:

- Dataset and Benchmarks:
  http://www.cvlibs.net/datasets/kitti-360
- Utilities and Scripts:
  https://github.com/autonomousvision/kitti360scripts
- Annotation Tool:
  https://github.com/autonomousvision/kitti360labeltool
- Video:
  https://www.youtube.com/watch?v=OonvYU5bx3s

Thank you!

http://autonomousvision.github.io

Federal Ministry of Education and Research

Federal Ministry for Economic Affairs and Energy

Overview of Publicly Available Datasets

	2D Annotations			3D Annotations					Coherency		Test
	#Smt. Img.	#Ins. Img.	Dense	#Smt. Pts.	#Ins. Pts.	FoV Azm.	FoV Plr.	#3D Bbox	Temporal	3D-2D	**Server**
CamVid	631	–	✓	–	–	–	–	–	✓	–	✗
DUS	1k	–	✓	–	–	–	–	–	✓	–	✗
CityScape (fine)	5k	5k	✓	–	–	–	–	–	✗	–	✓
CityScape (coarse)	20k	20k	✗	–	–	–	–	–	✗	–	✓
Mapillary Vistas	25k	25k	✓	–	–	–	–	–	✗	–	✗
CityScape-VPS	3k	3k	✓	–	–	–	–	–	✓	–	✗
KITTI-STEP	19k	19k	✓	–	–	–	–	–	✓	–	✓
Toronto-3D	–	–	–	78.3M	–	360°	40°	–	–	–	✗
Paris-Lille-3D	–	–	–	143.1M	–	360°	40°	–	–	–	✓
DublinCity	–	–	–	260M	–	-	-	–	–	–	✗
Semantic3D.net	–	–	–	4.0B	–	360°	360°	–	–	–	✓
SemanticKITTI	–	–	–	4.5B	–	360°	26.8°	–	–	–	✓
Argoverse	–	–	–	–	–	–	–	993k	–	–	✗
Waymo	–	–	–	–	–	–	–	12M	–	–	✓
A*3D	–	–	–	–	–	–	–	230k	–	–	✗
KITTI	200	200	✓	–	–	–	–	200k	✗	✗	✓
ApolloScape	144k	90k	✓	–	–	–	–	70k	✗	✗	✓
nuScenes	93k	93k	✓	1.2B	78.9M	360°	40°	1.2M	✗	✗	✓
A2D2	41k	41k	✓	387.1M	23.8M	60°	30°	43k	✗	✓	✗
SemKITTI-DVPS	23k	23k	✗	4.5B	400M	360°	26.8°	–	✓	✓	✓
KITTI-360	2× 78k	2× 78k	✓	1.0B	172.4M	360°	120°	68k	✓	✓	✓

http://www.cvlibs.net/datasets/kitti-360/