Simulating data can be beneficial when data is scarce or annotation is costly [1,2]. Previous work simulates large quantities of random scenes, e.g., [3,4].

Can we automatically learn to simulate better data for a particular task? Can we find a better trade-off between diversity and volume of the data? Are the true data generating parameters the best for training prediction models?

We explore these questions with a reinforcement-learning based approach to automatically adjust simulation parameters.

Simulator and sampling are non-differentiable
Resort to reinforcement learning
Vanilla policy gradients for optimization

We want to solve the following bi-level optimization problem.

We simulate:
- Road and intersection
- Houses on the side
- Cars
- Weather


Car-counting on simulated data:
- Ground truth data-generating parameters are given.
- Train CNN to count all instances of 5 different types of cars
- Model achieves lower error on the unseen test set than the mean error obtained using the ground truth simulation parameters
- Robust to simulation parameter initialization
- Model approximates "upper bound" and outperforms random parameters

Semantic segmentation on real data:
- Experiments on KITTI
- Model outperforms random policy parameters and random search on real data
- Model outperforms validation set parameters on simulated data

**References**