

Data-Driven Datasets

Deep Active Learning for Autonomous Vehicles, ML and Beyond

Adam Lesnikowski



[@lesnikow](https://twitter.com/lesnikow)

Senior Software Perception Engineer, NVIDIA

NVIDIA GTC Silicon Valley 2019 Wednesday March 20th, 2019

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Motivations



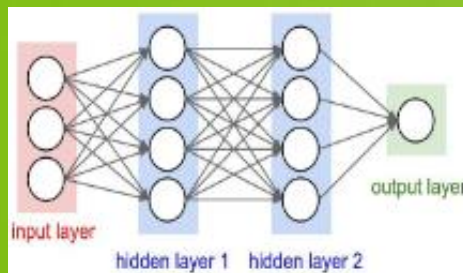
+



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So how do we go from:



Xu et. al



+



Not All Data are Created Equally...



vs.



Some Are Much More Informative

Two Motivating Challenges

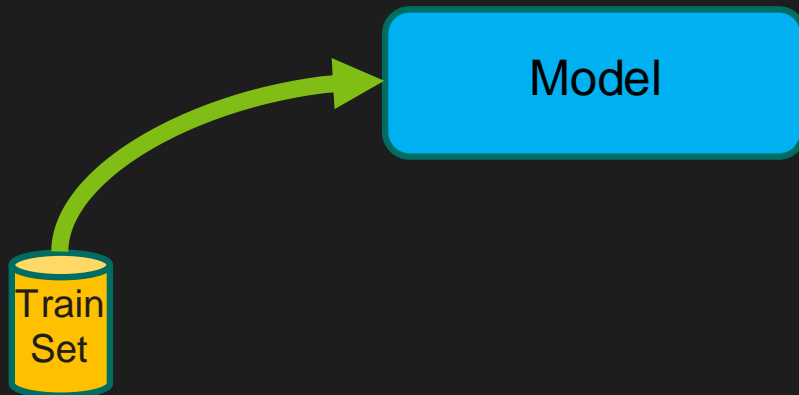
Two Motivating Challenges

1. How do we **improve the cost complexity of** our labeling?

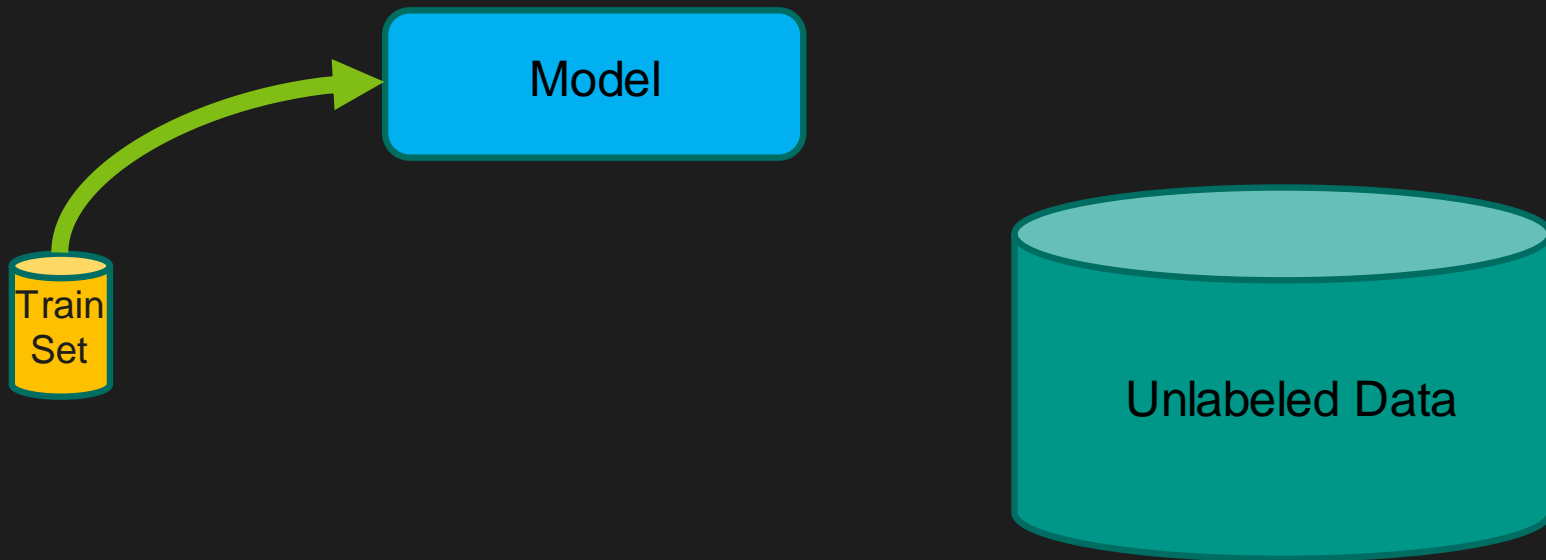
Two Motivating Challenges

1. How do we **improve the cost complexity** of our labeling?
2. How do we find the **most informative** unlabeled images to get the safest autonomous vehicles possible?

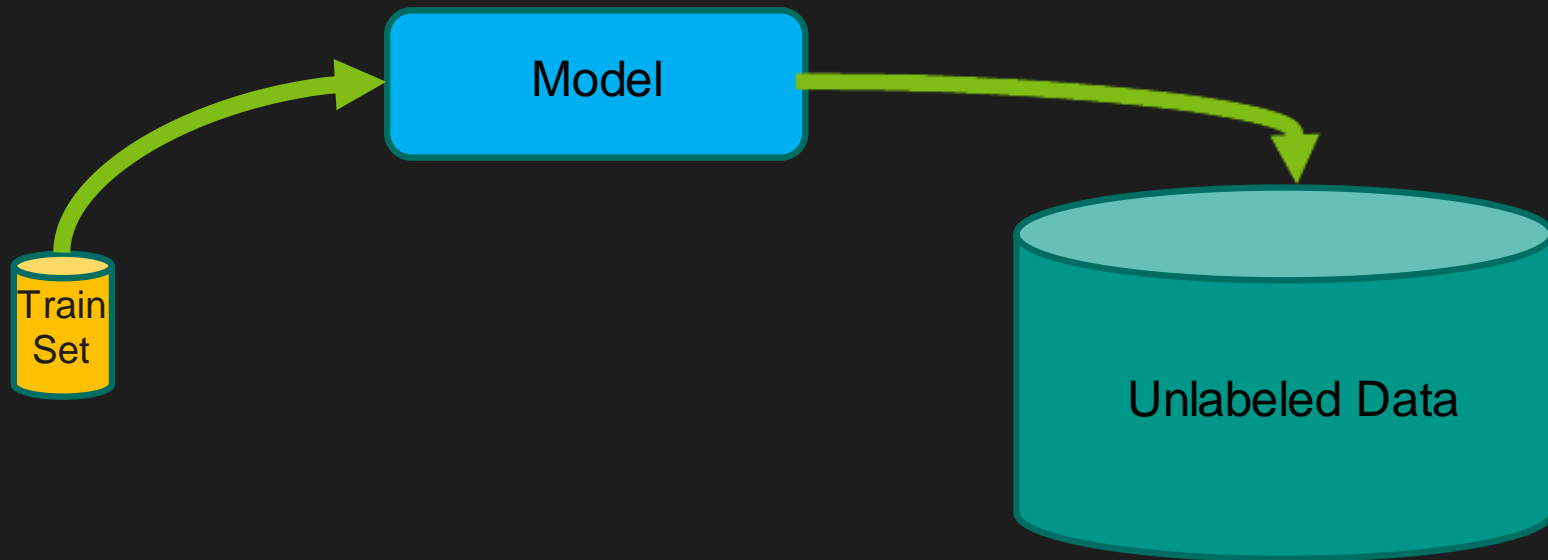
Traditional Machine Learning



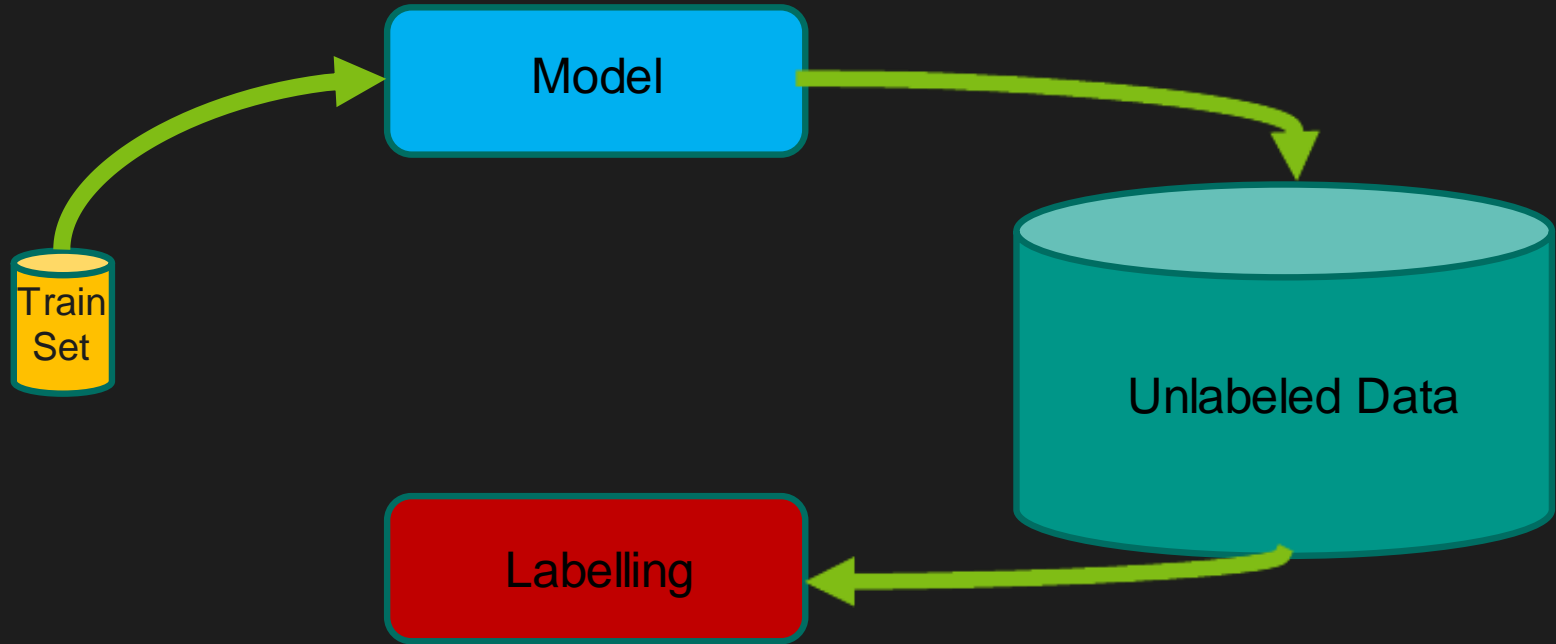
The Active Learning Approach



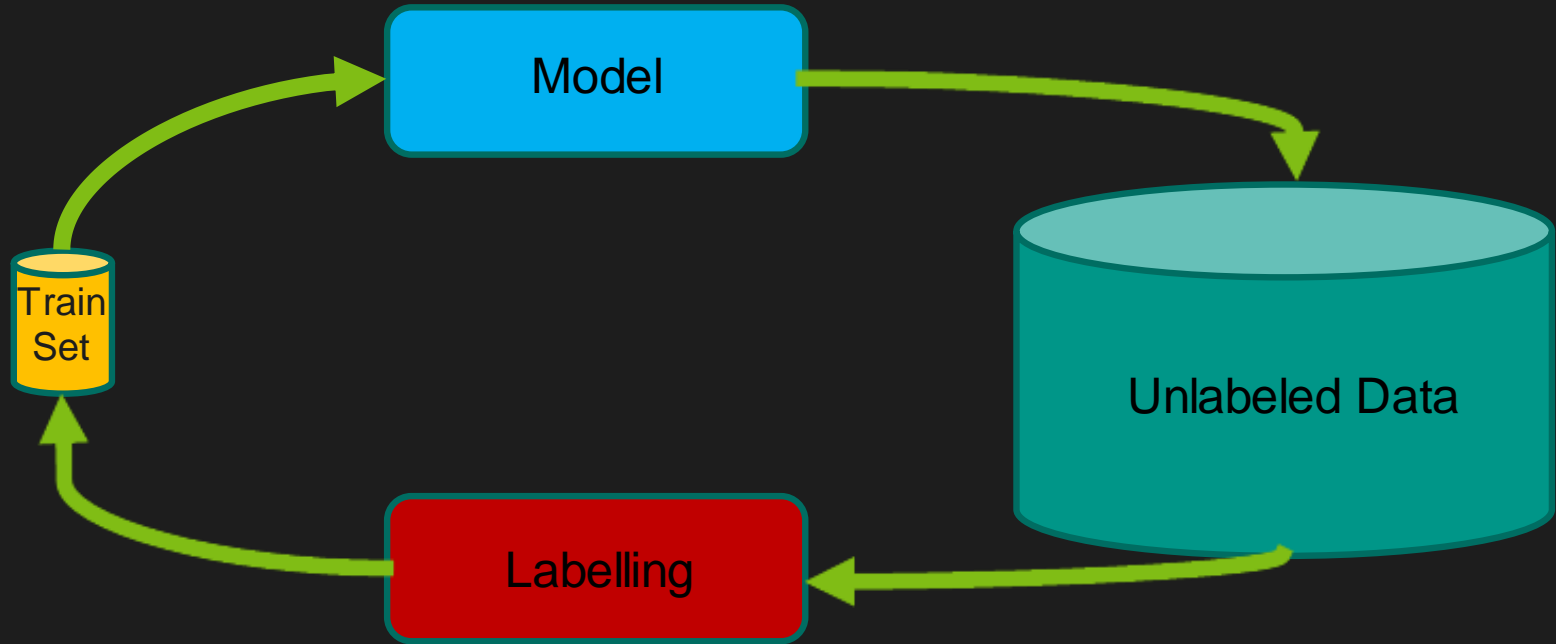
The Active Learning Approach



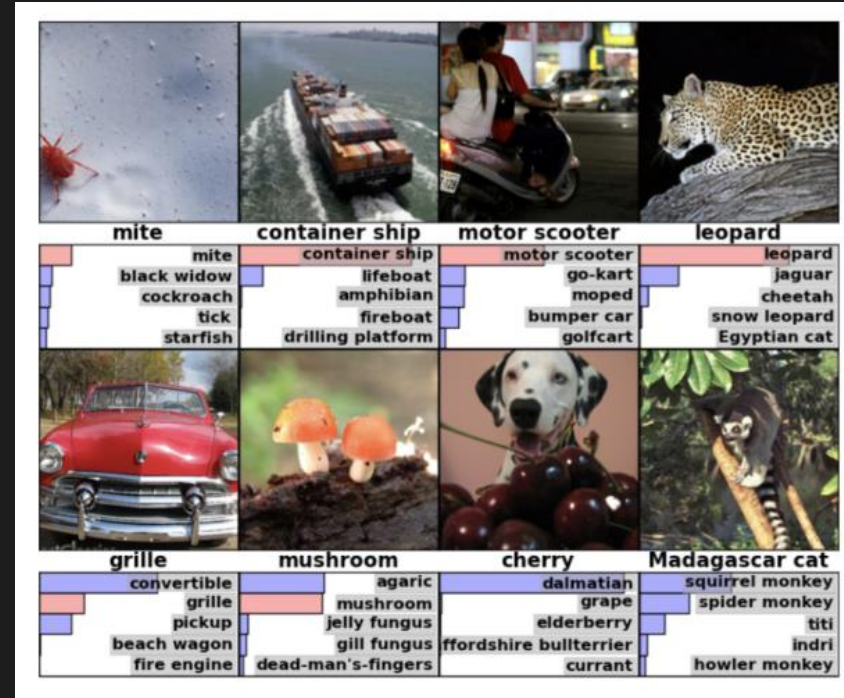
The Active Learning Approach



The Active Learning Approach



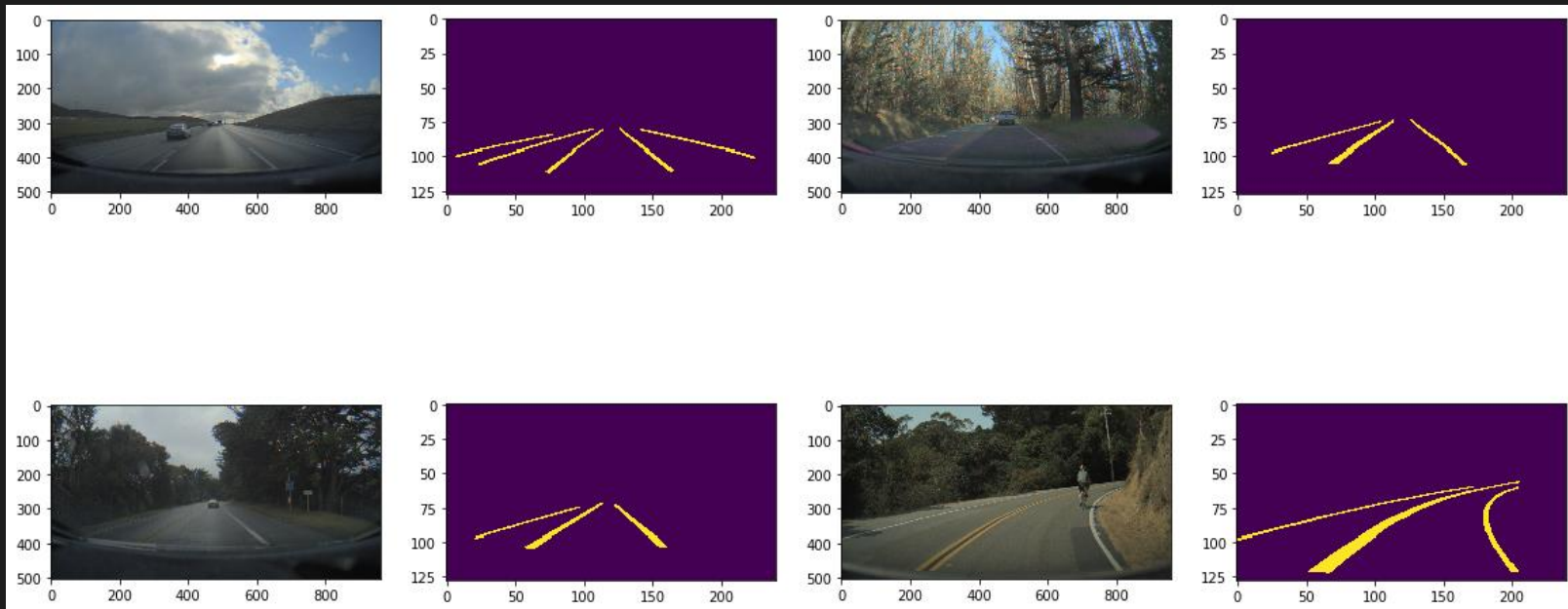
Datasets: Classification



Datasets: MNIST hand-drawn digits, 60K train 10K test split , ImageNet 1K: ~1.3M train images, 50K test images.

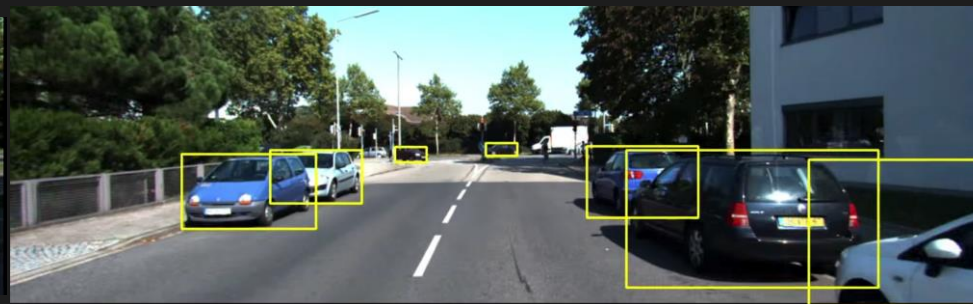
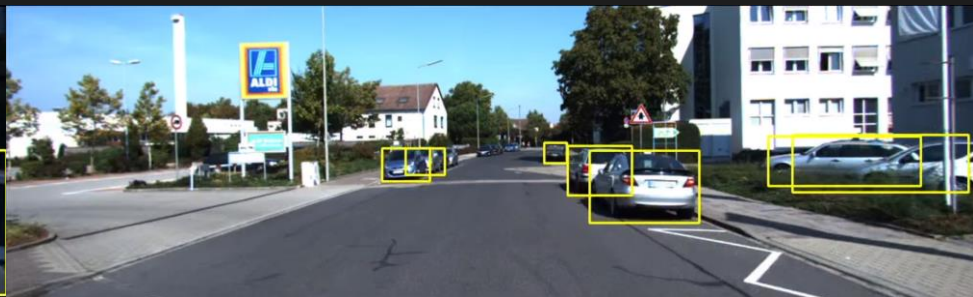
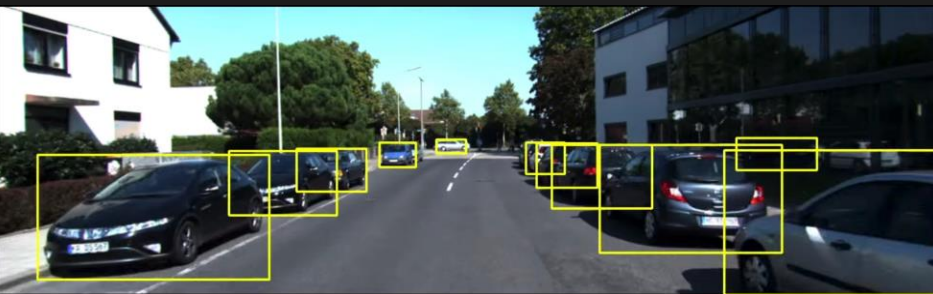
Datasets: Lane Segmentation

Dataset: 100K train, 10K val split with pixel segmentations for lanes

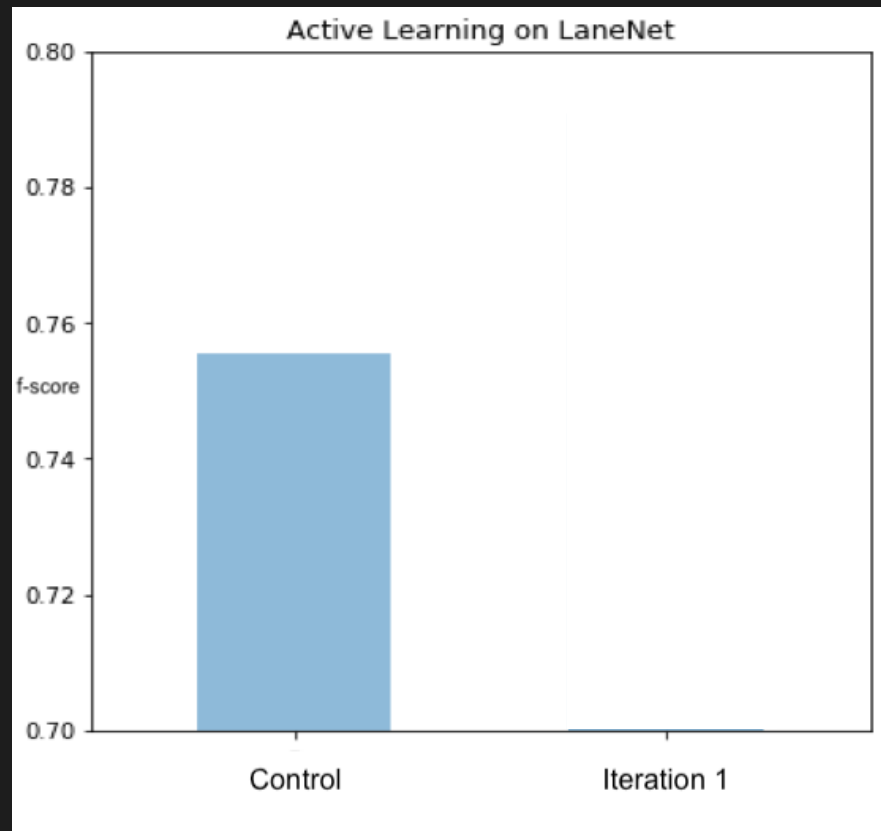


Datasets: Road Scene Object Detection

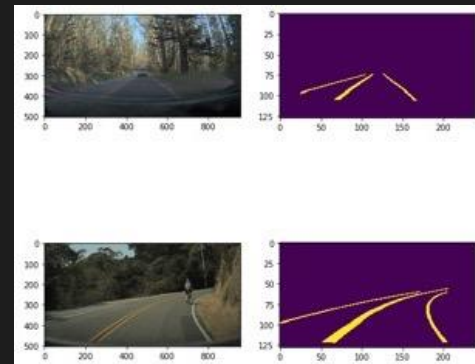
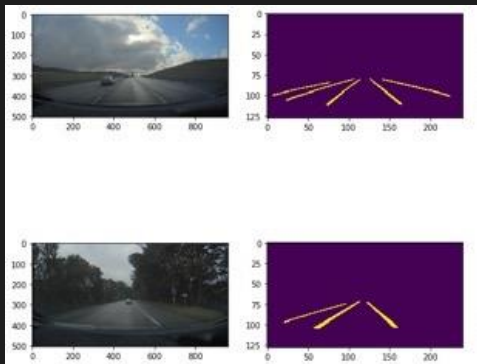
Dataset: 150K train, 10K val split, with bounding box labels



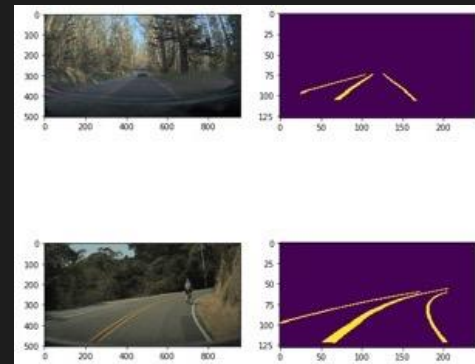
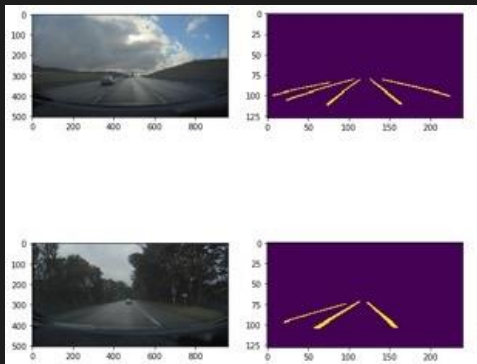
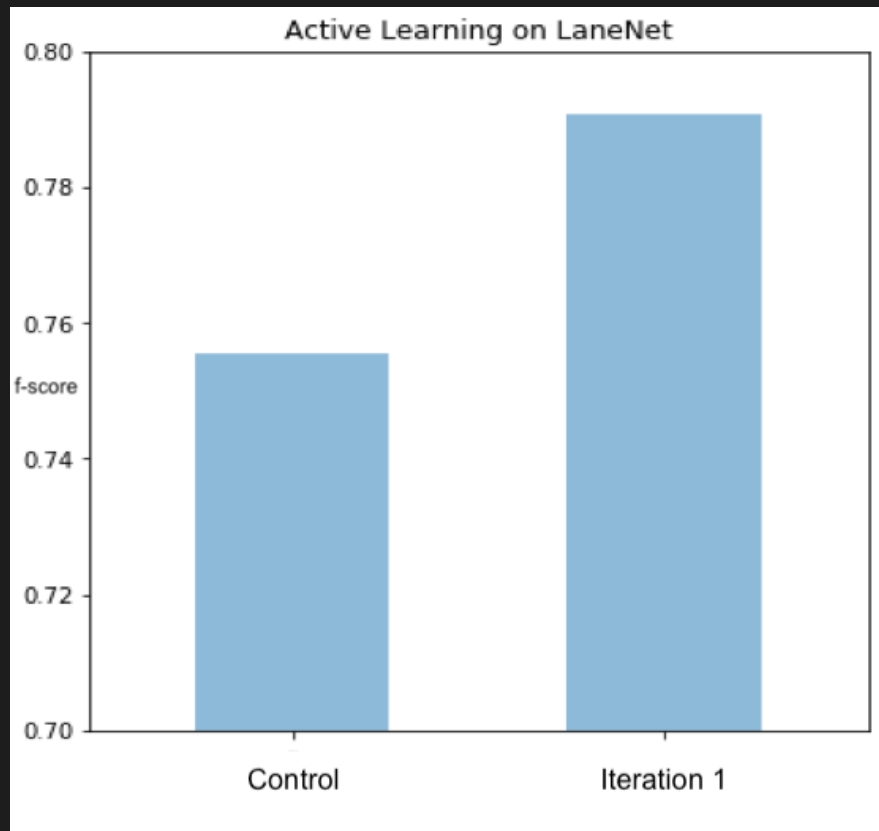
Segmentation Results



Results of active learning on pixel segmentation for road markings



Segmentation Results



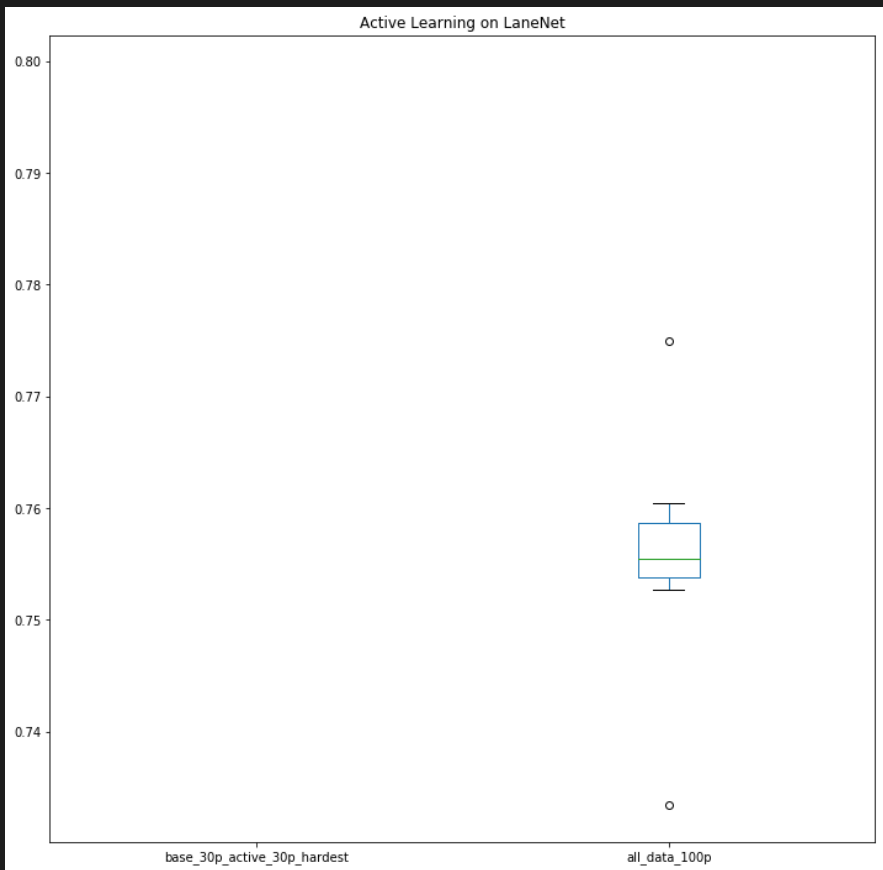
Results of active learning on pixel segmentation for road markings

[Lesnikowski, 2017]

Segmentation Results

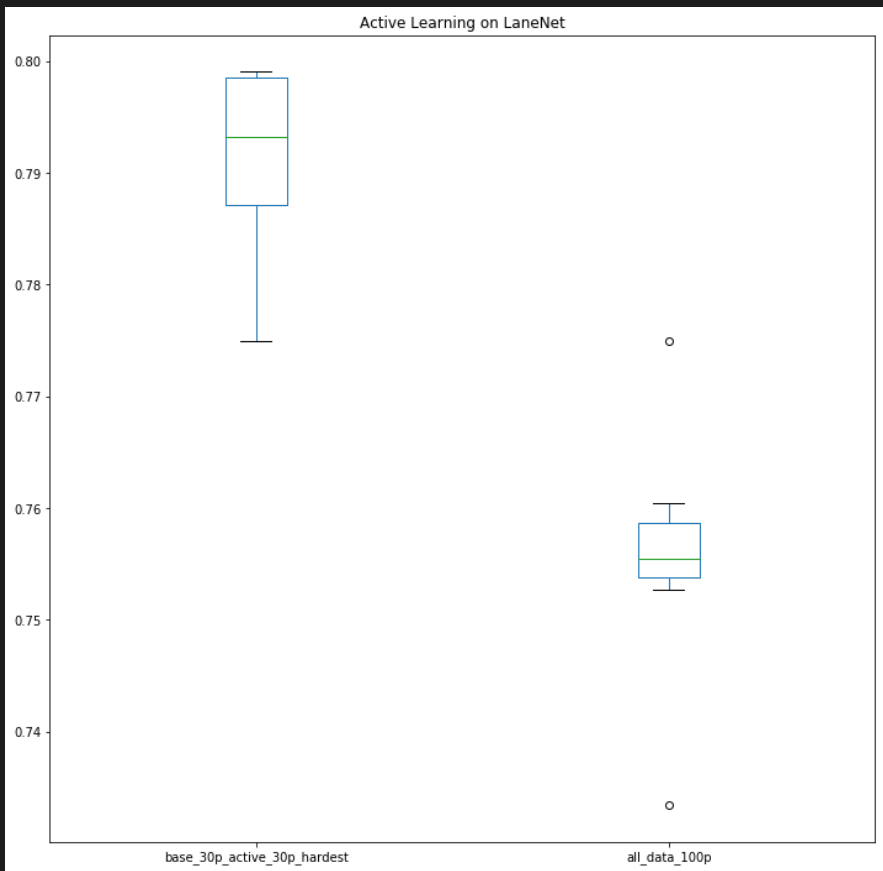
Robustness analysis. Results on segmentation for road markings, across multiple runs of the active learning cycle.

Segmentation Results



Robustness analysis. Results on segmentation for road markings, across multiple runs of the active learning cycle.

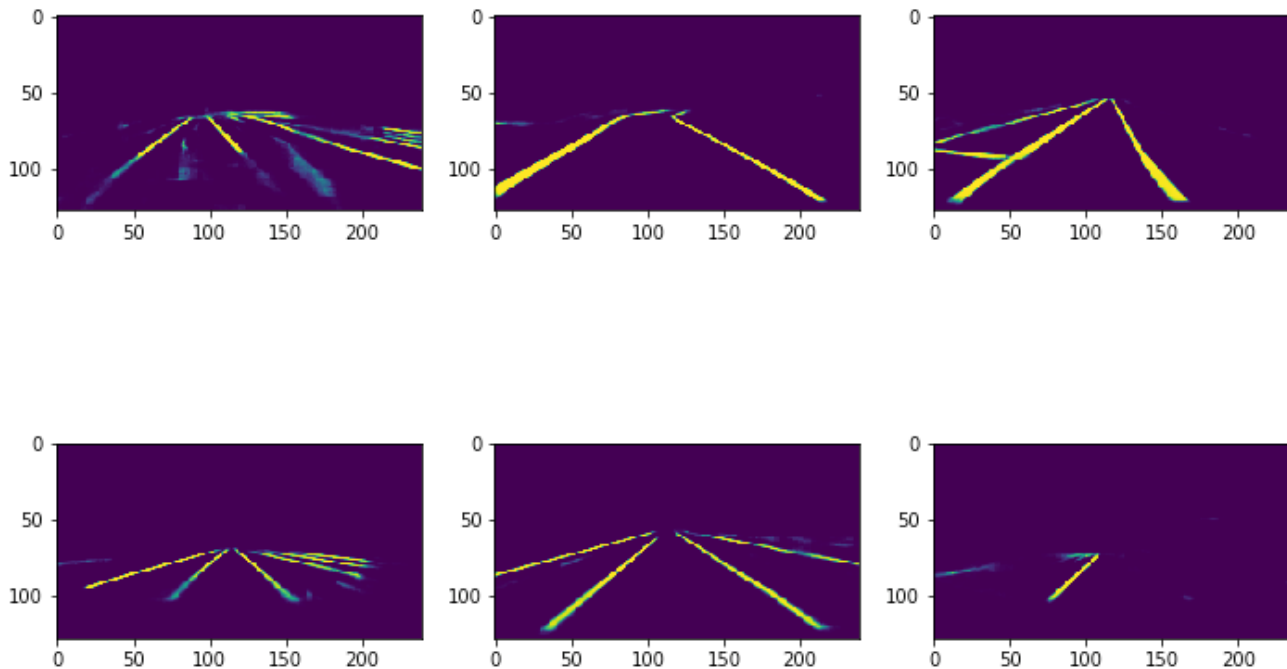
Segmentation Results



Robustness analysis. Results on segmentation for road markings, across multiple runs of the active learning cycle.

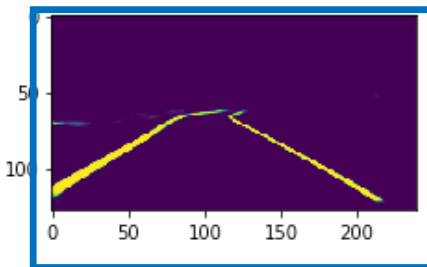
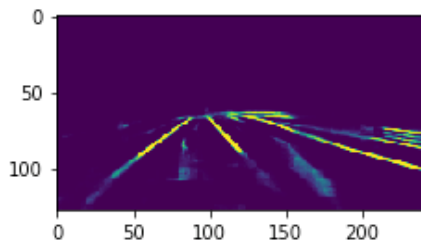
[Lesnikowski, 2017]

Segmentation Results

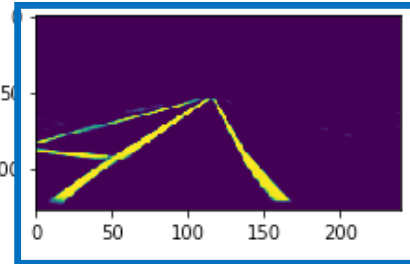


Sample predictions from our network

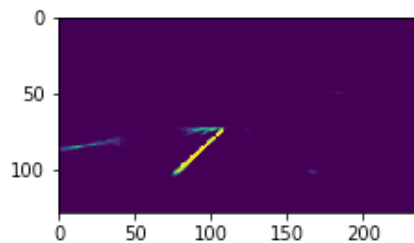
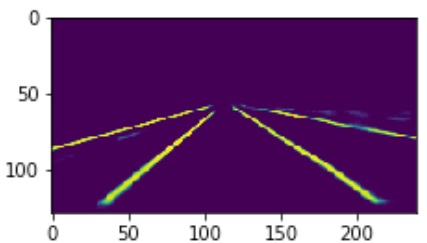
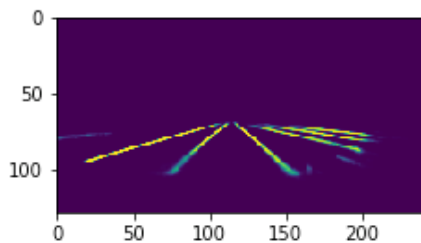
Segmentation Results



Low confusion

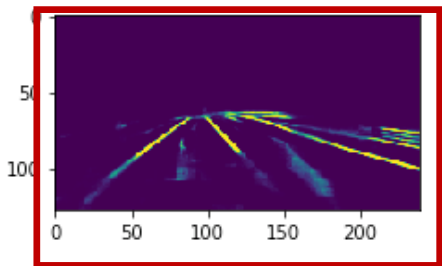


Low confusion

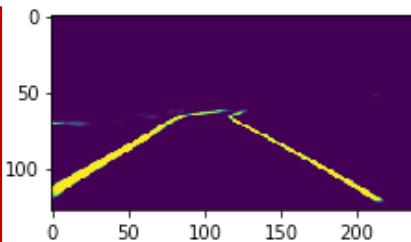


Sample predictions from our network

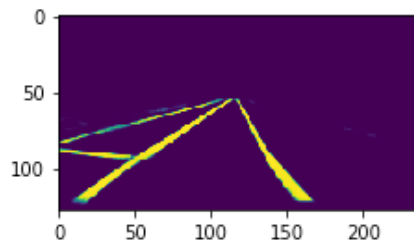
Segmentation Results



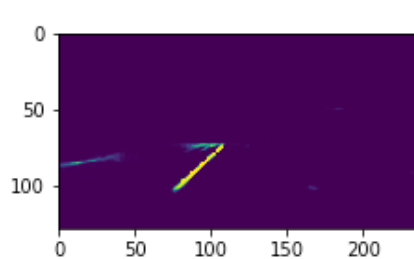
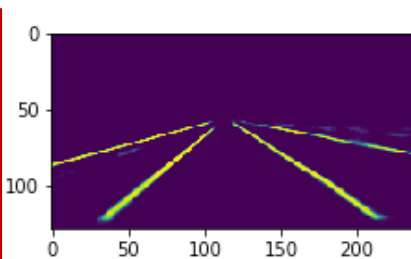
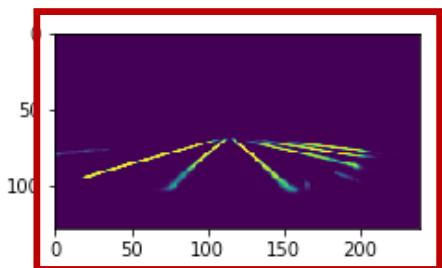
High confusion



Low confusion



Low confusion



Sample predictions from our network

Detection Results

100% of the samples were detected.

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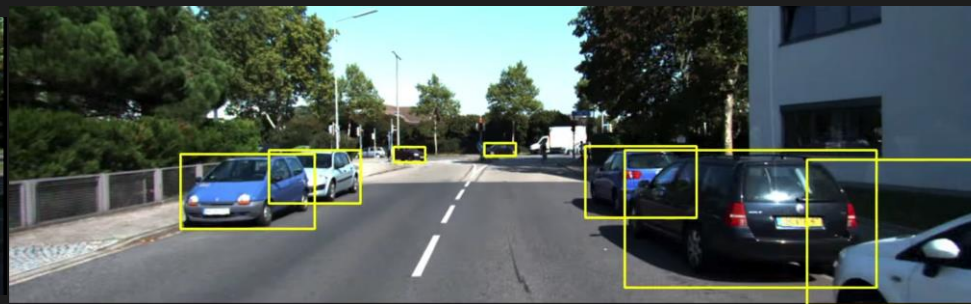
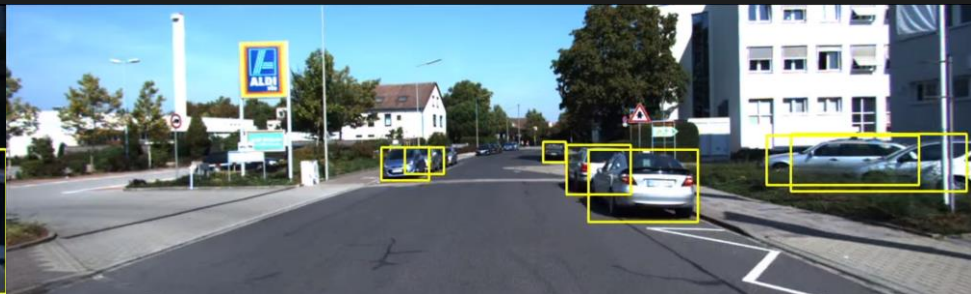
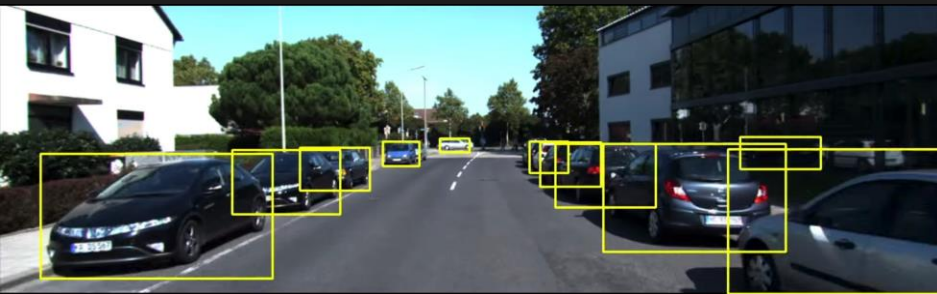
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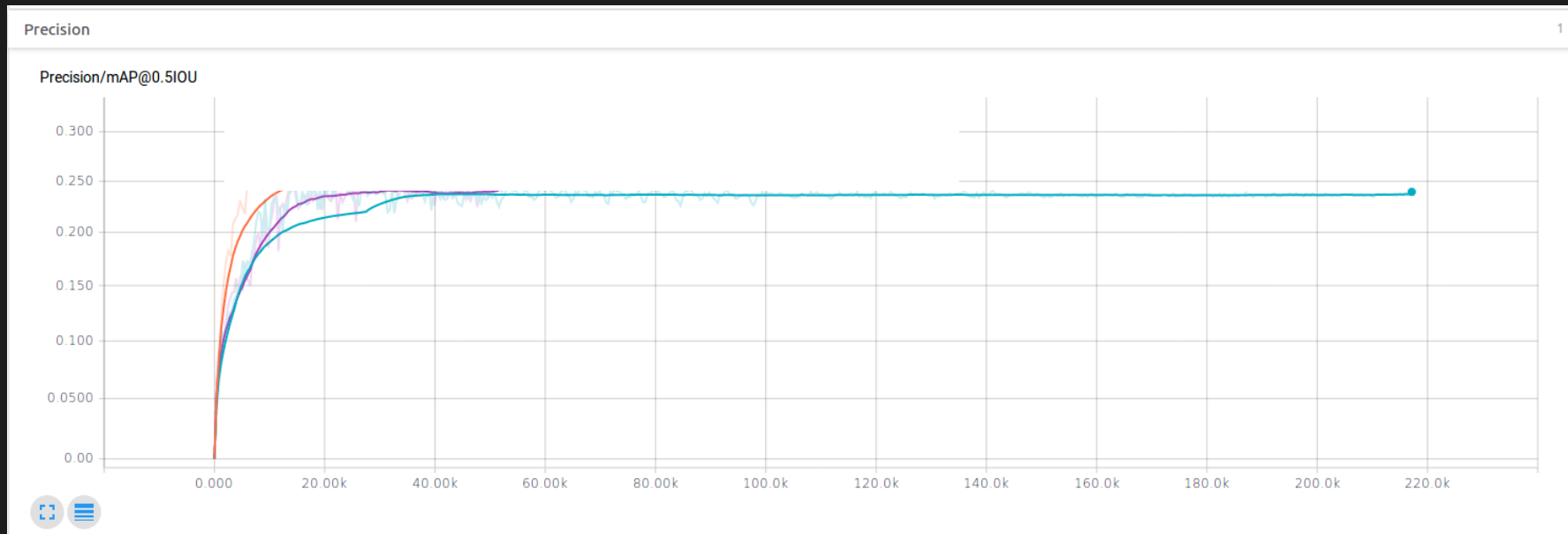
100% of the samples were detected.

100% of the samples were detected.

Detection Experiment Setup

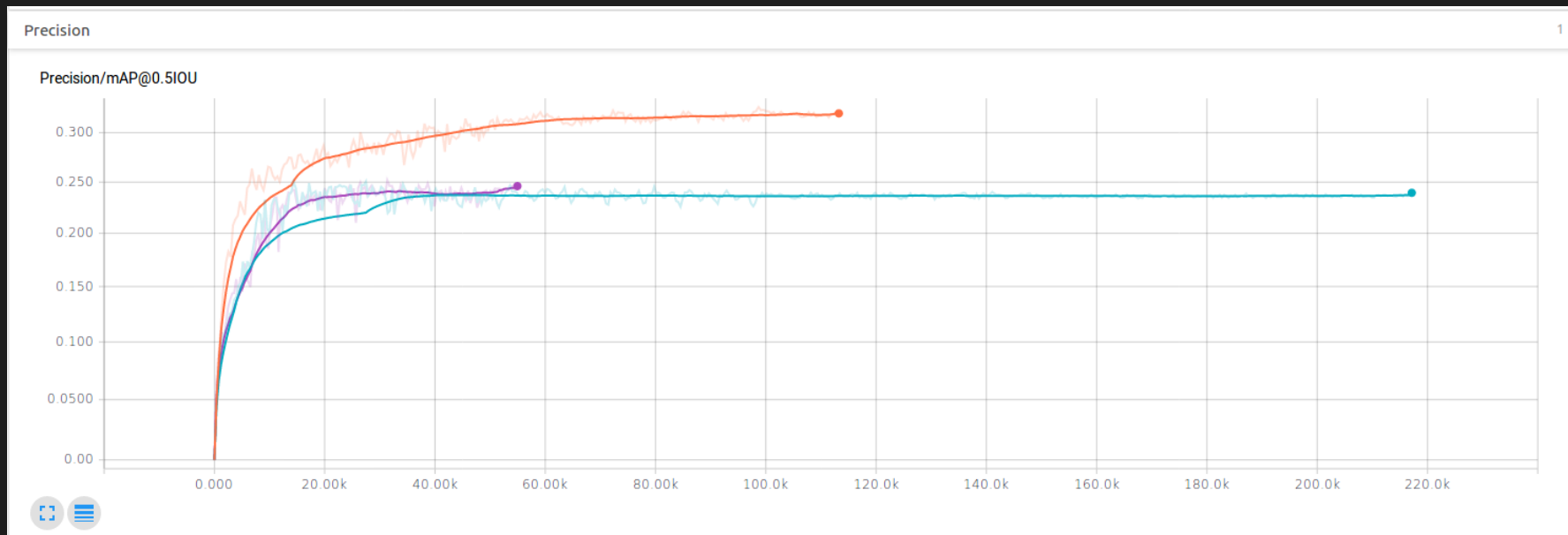


Detection Results



Object detection performance. mAP as as function of epochs, for base model (blue), random strategy (purple) and active strategy (orange).

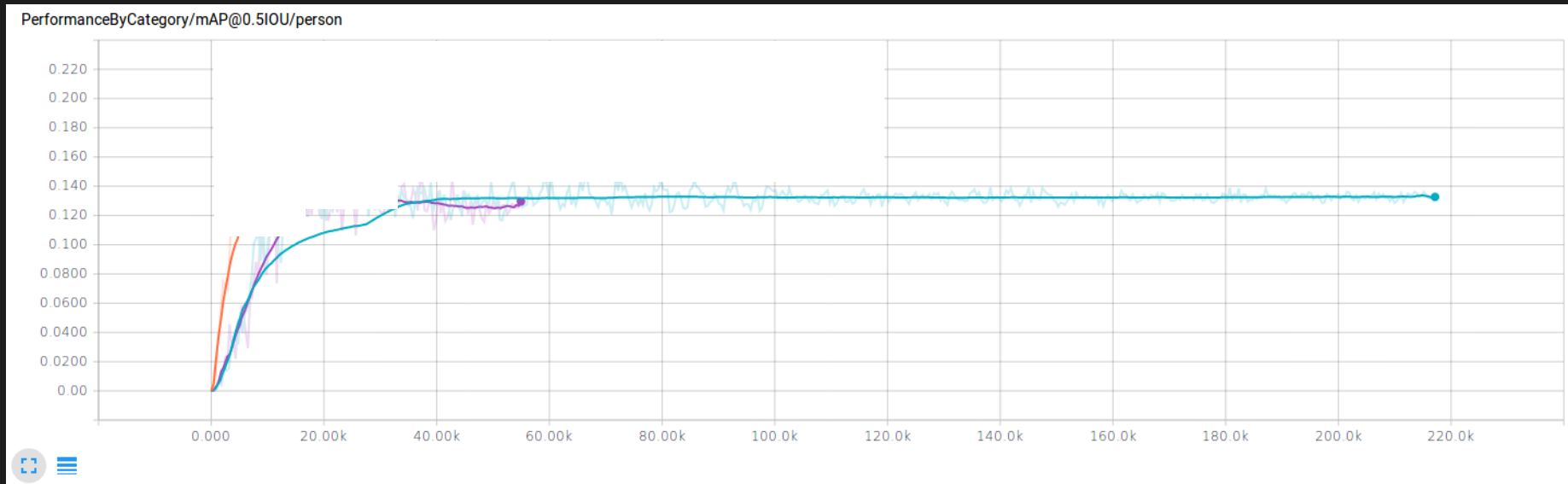
Detection Results



Object detection performance. mAP as as function of epochs, for base model (blue), random strategy (purple) and active strategy (orange).

[Lesnikowski, Plump, 2017]

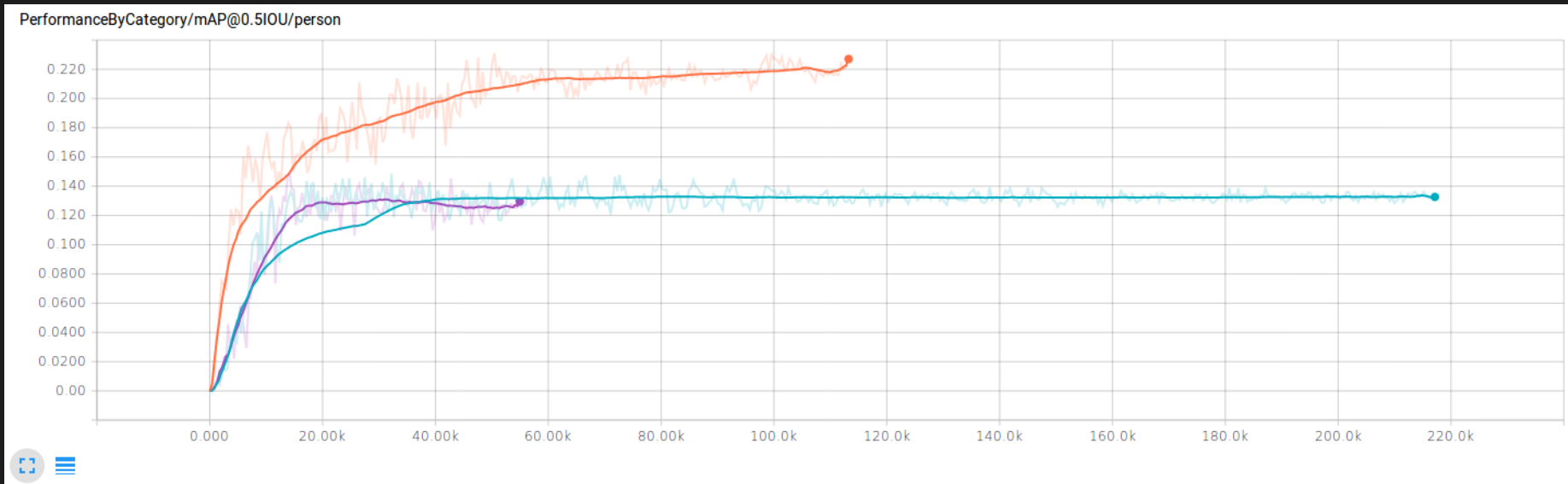
Detection Results



Object detection performance. mAP for persons as as function of epochs, for base model (blue), random strategy (purple) and active strategy (orange).

[Lesnikowski, Plump, 2017]

Detection Results



Object detection performance. mAP for persons as as function of epochs, for base model (blue), random strategy (purple) and active strategy (orange).

[Lesnikowski, Plump, 2017]

Detection Acquisition Examples

Sample predictions from our object detection model.

Detection Acquisition Examples

Low Confusion

Model 1



Model 2



Sample predictions from our object detection model.

Detection Acquisition Examples

Low Confusion

Model 1

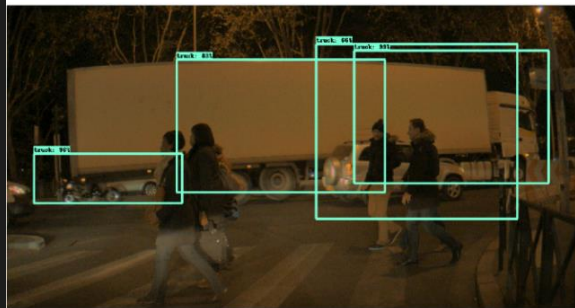


Model 2

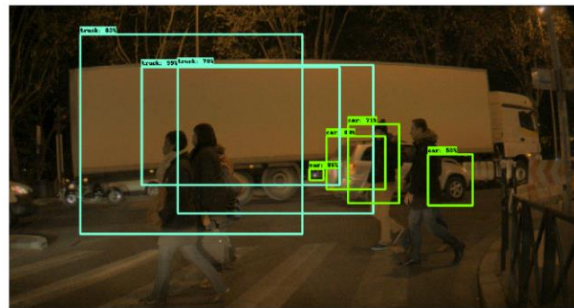


High Confusion

Model 1

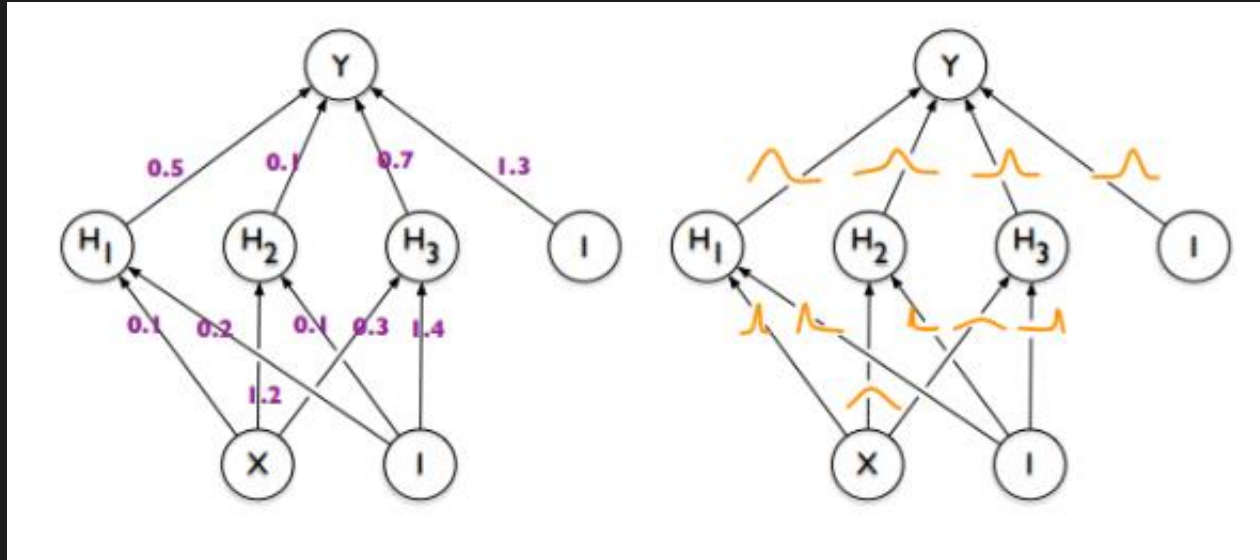


Model 2



Sample predictions from our object detection model.

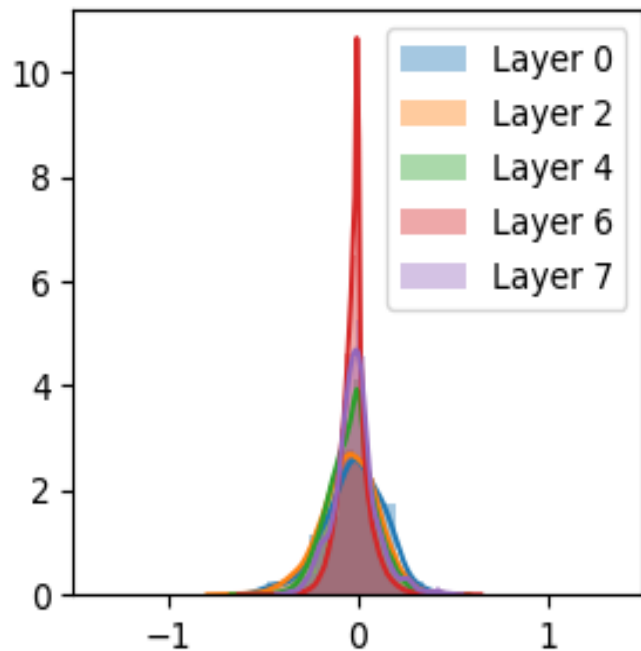
Bayesian Deep Active Learning for Autonomous Vehicles



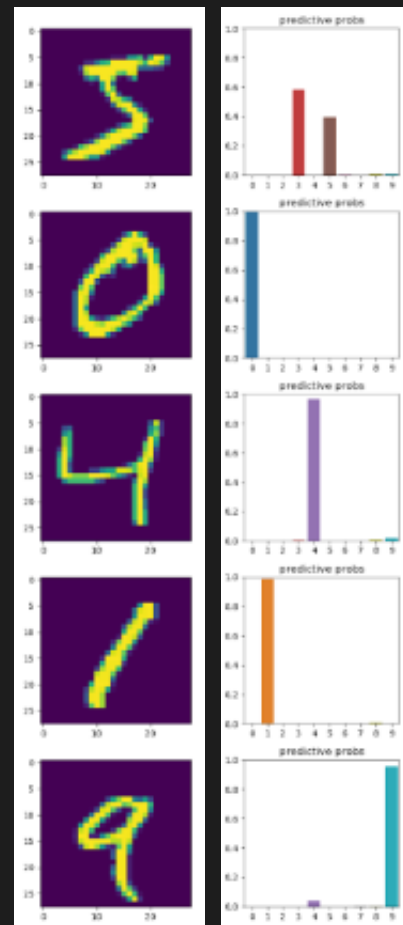
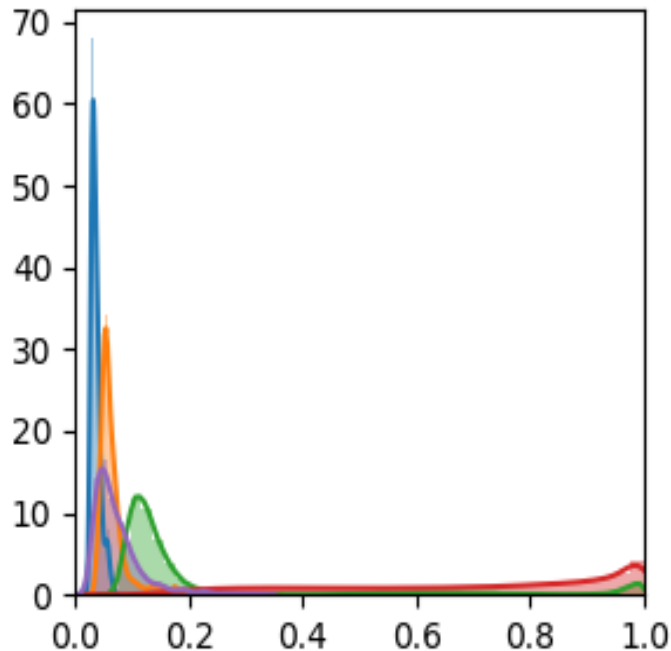
TensorFlow Probability

MNIST

weight means



weight stddevs



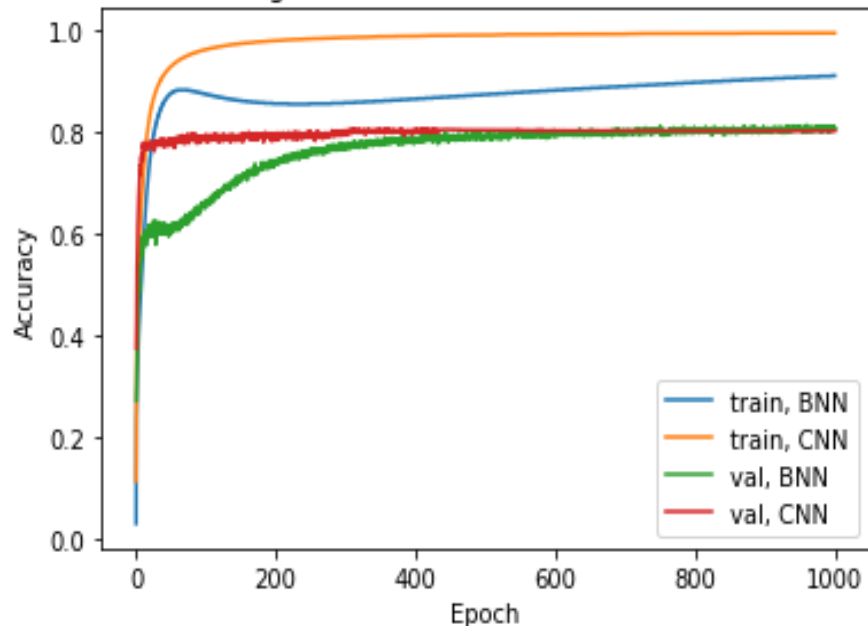
Network: ResNet18 Training: 1000 epochs Testing Accuracy: 81%

[Example incorporated into the official TFP repository.](#)

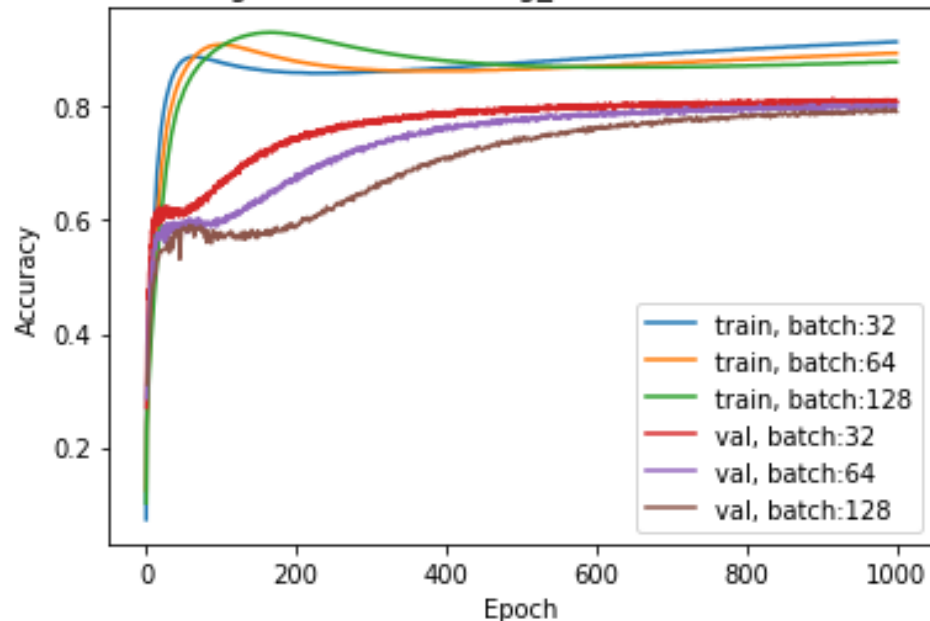
TensorFlow Probability

CIFAR-10

Training and Validation (batch = 32, lr=1e-4)

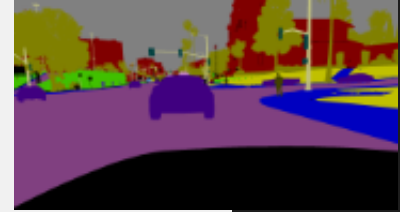
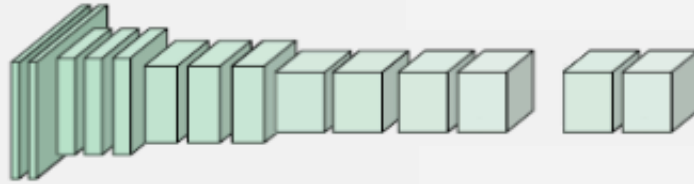


Training and Validation (log_var~ $N(-9, 0.1)$, lr=1e-4)

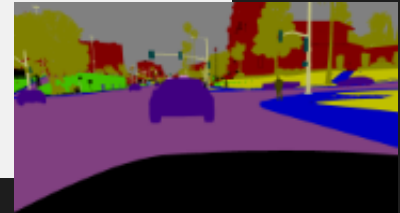
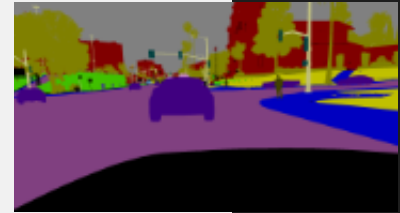
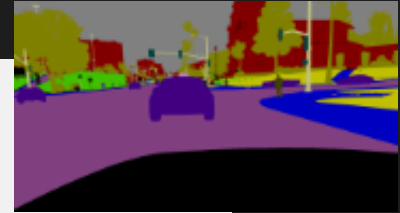
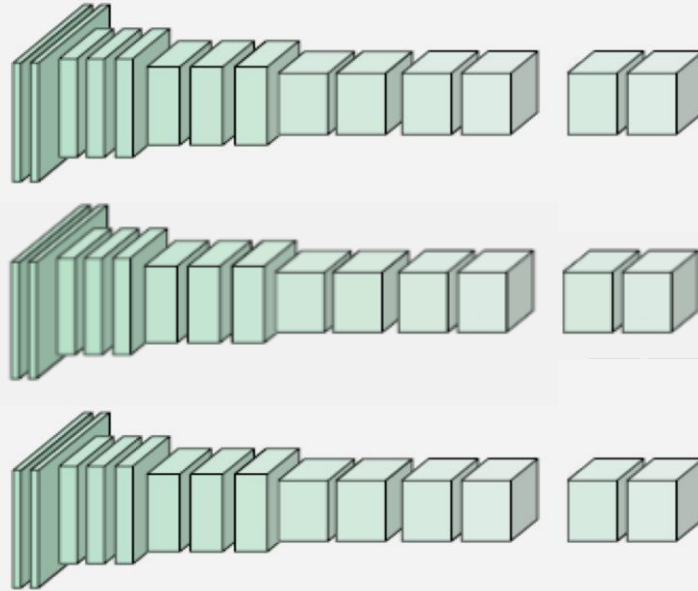


Network: ResNet18 Training: 1000 epochs Testing Accuracy: 81%

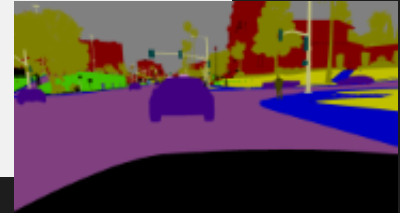
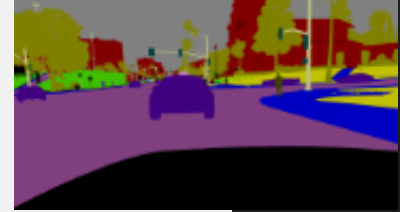
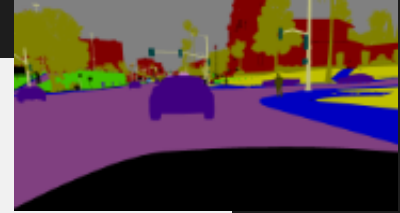
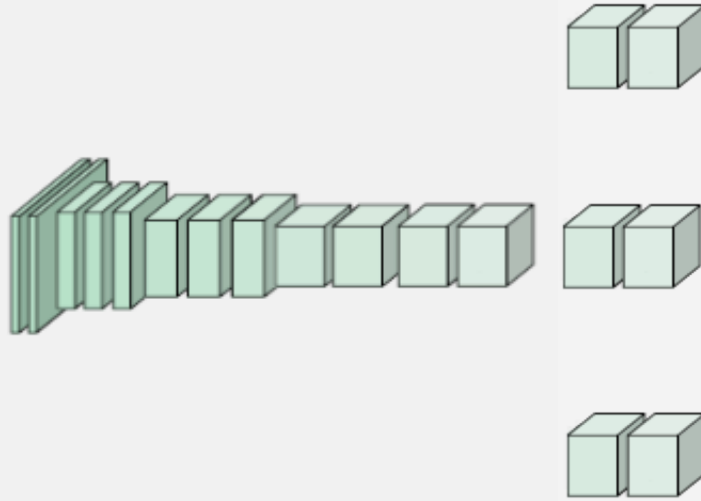
Bayesian Regularized Ensembles for Segmentation



Bayesian Regularized Ensembles for Segmentation



Bayesian Regularized Ensembles for Segmentation

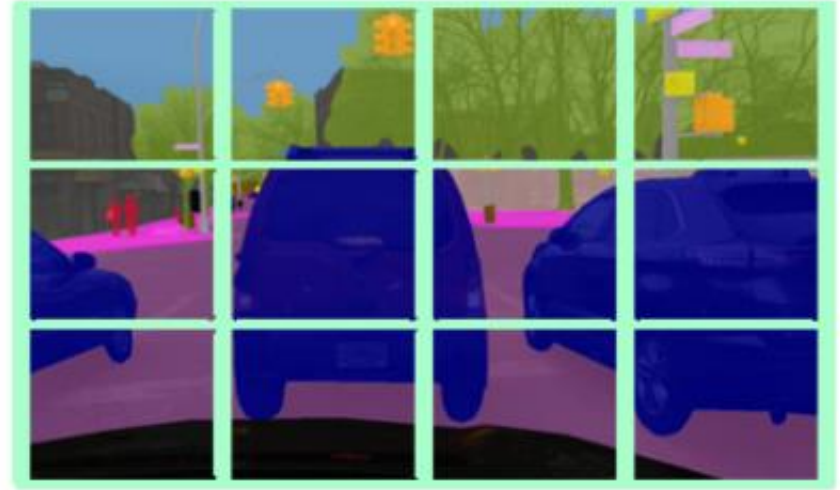


Segmentation: Experimental Setup



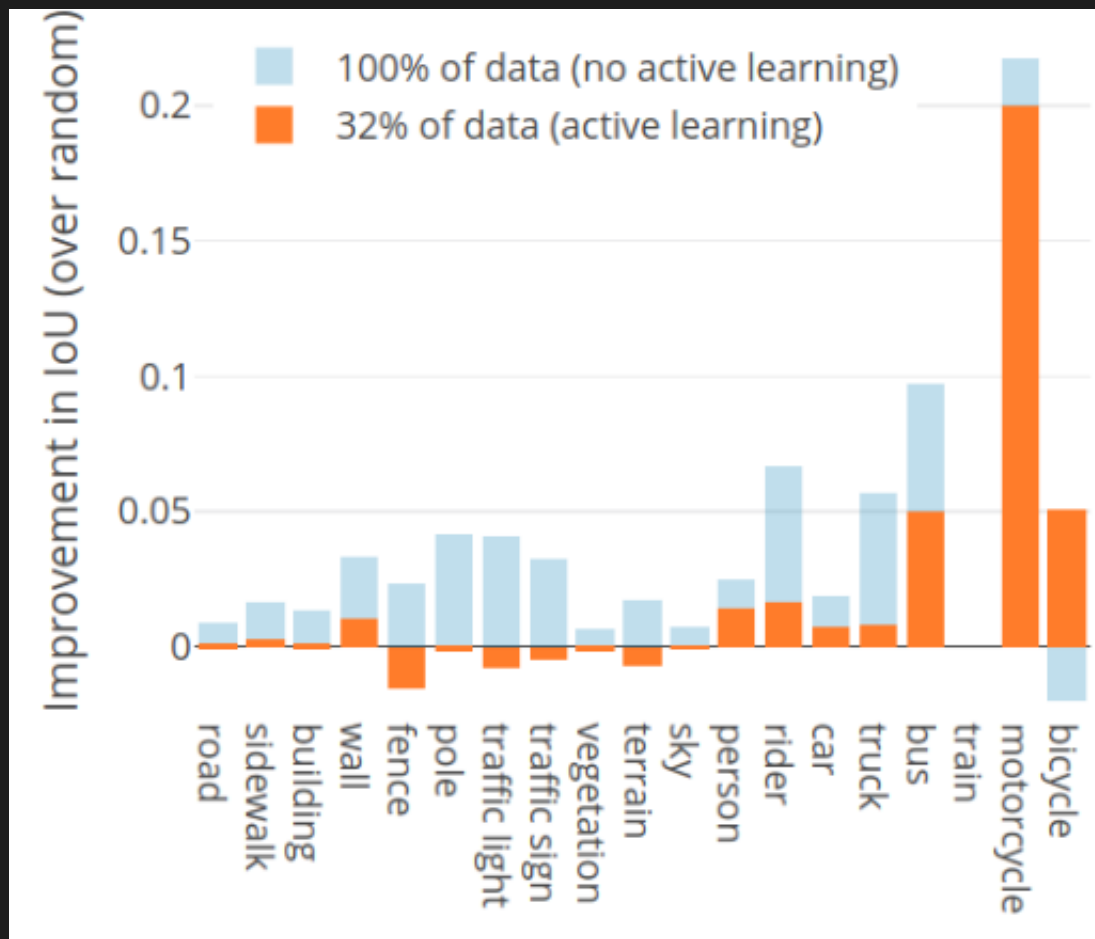
Pretrain on CityScapes, evaluate active learning on BDD100k

Segmentation: Experimental Setup

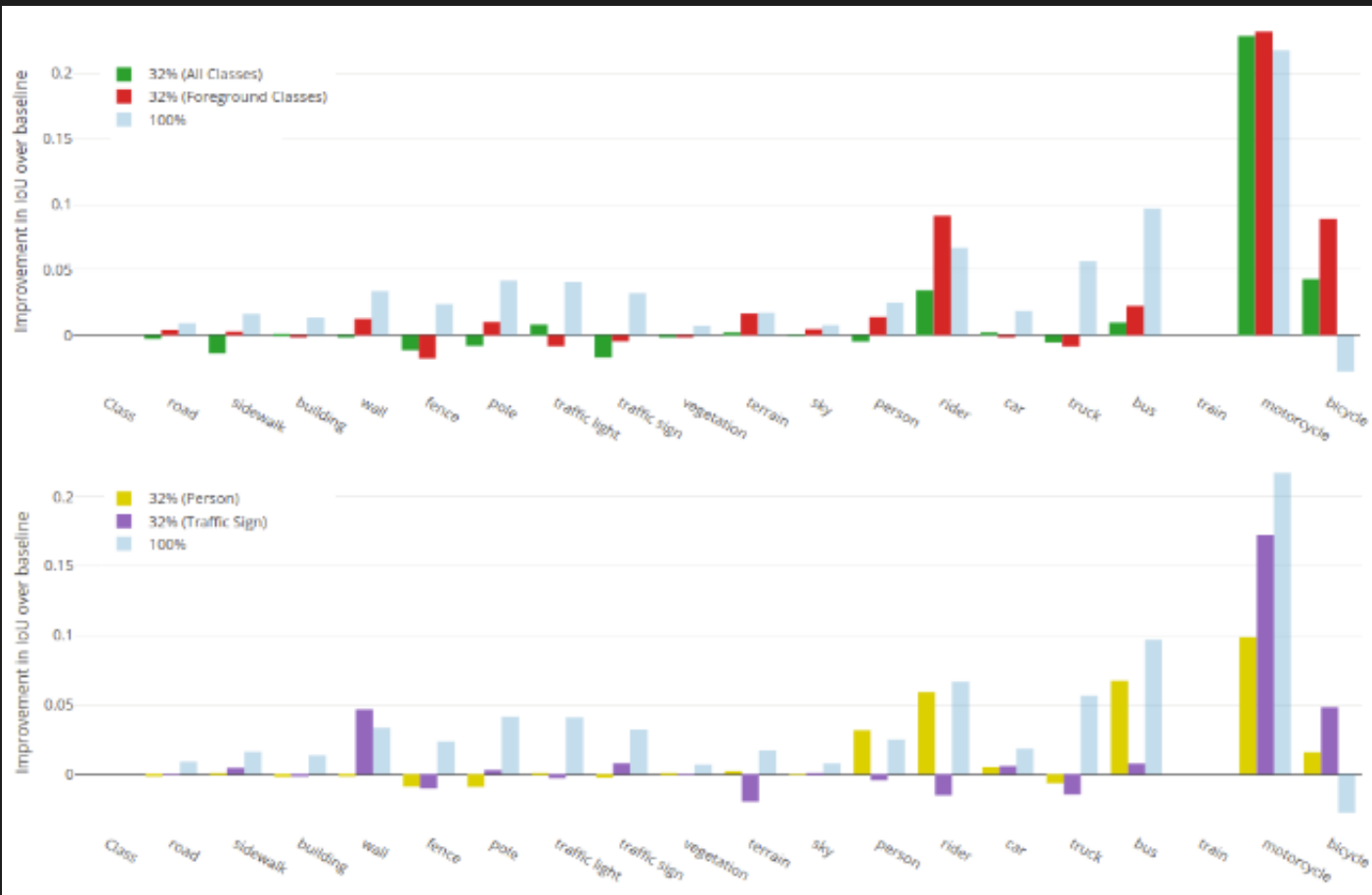


Partition image into a 4x3 grid, giving 12 crops

Results: Class-wise Improvements

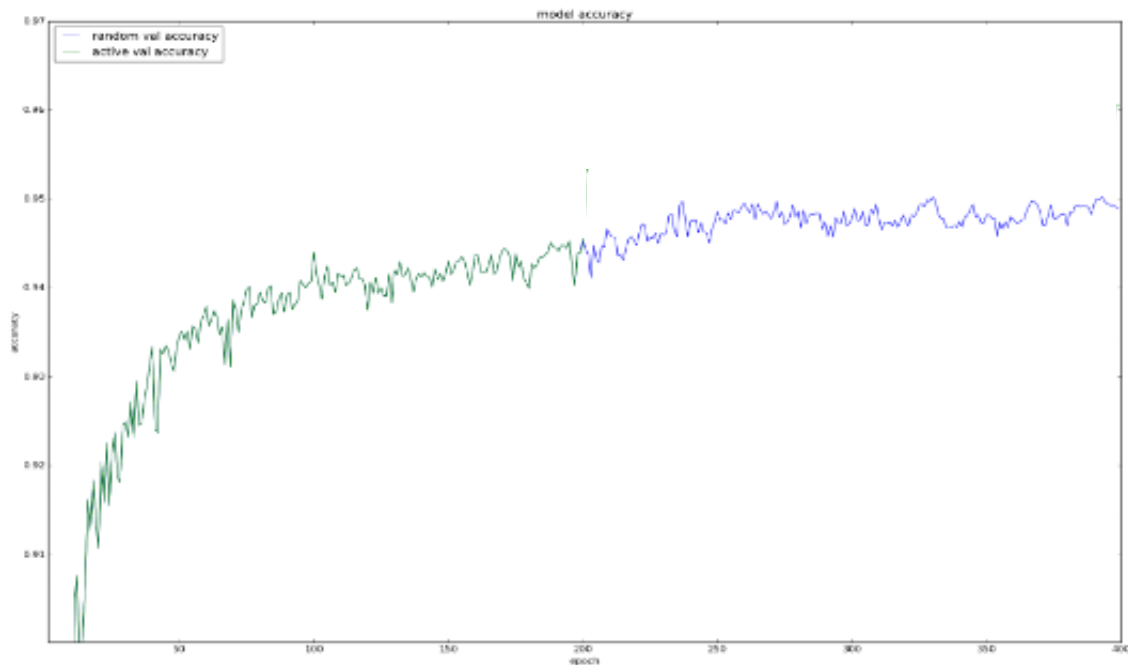


Results: Targeting Classes



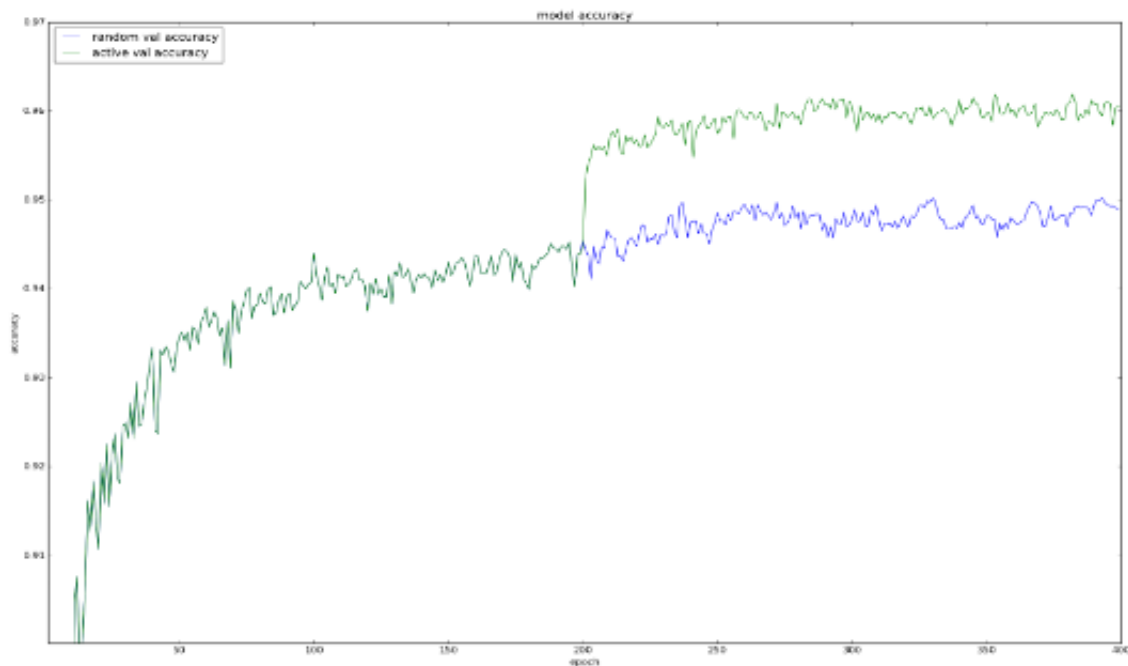
[Chitta, Alvarez,
Lesnikowski
forthcoming]

Classification Results



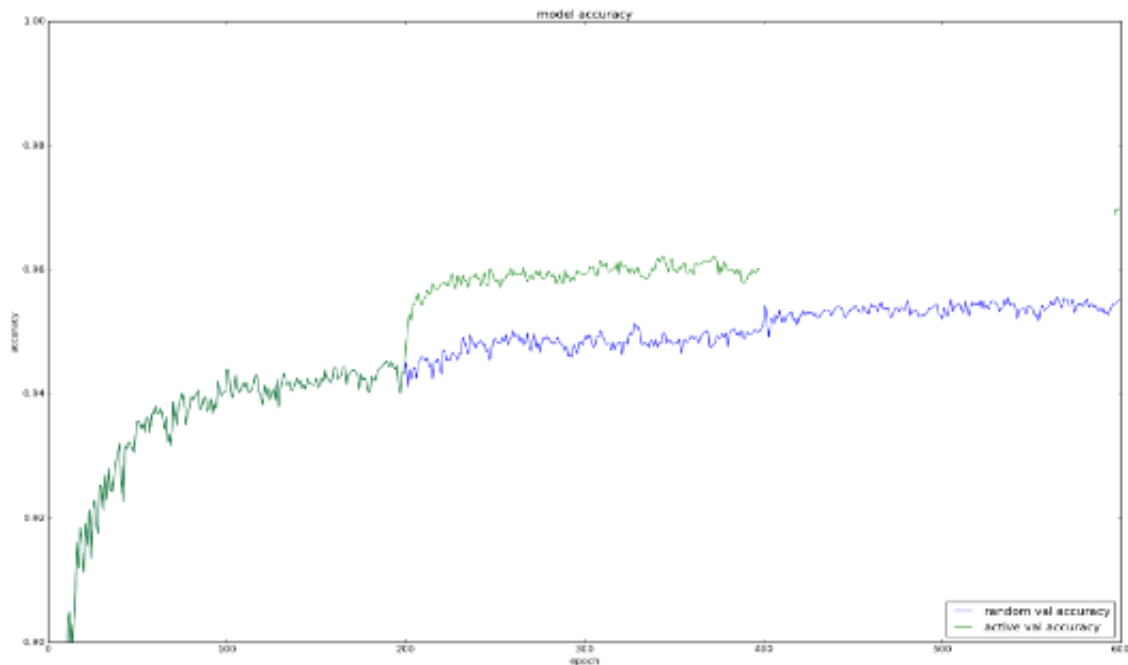
Classification results after one active learning cycle with an entropy policy.
Random baseline (blue) versus active strategy (green).

Classification Results



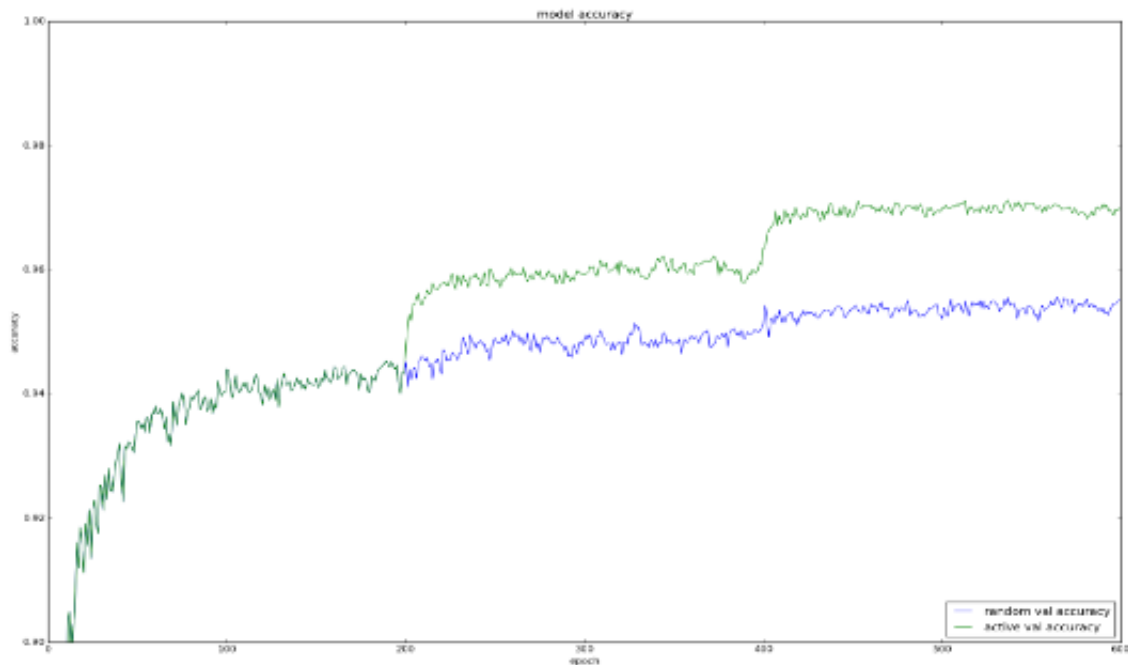
Classification results after one active learning cycle with an entropy policy.
Random baseline (blue) versus active strategy (green).

Classification Results



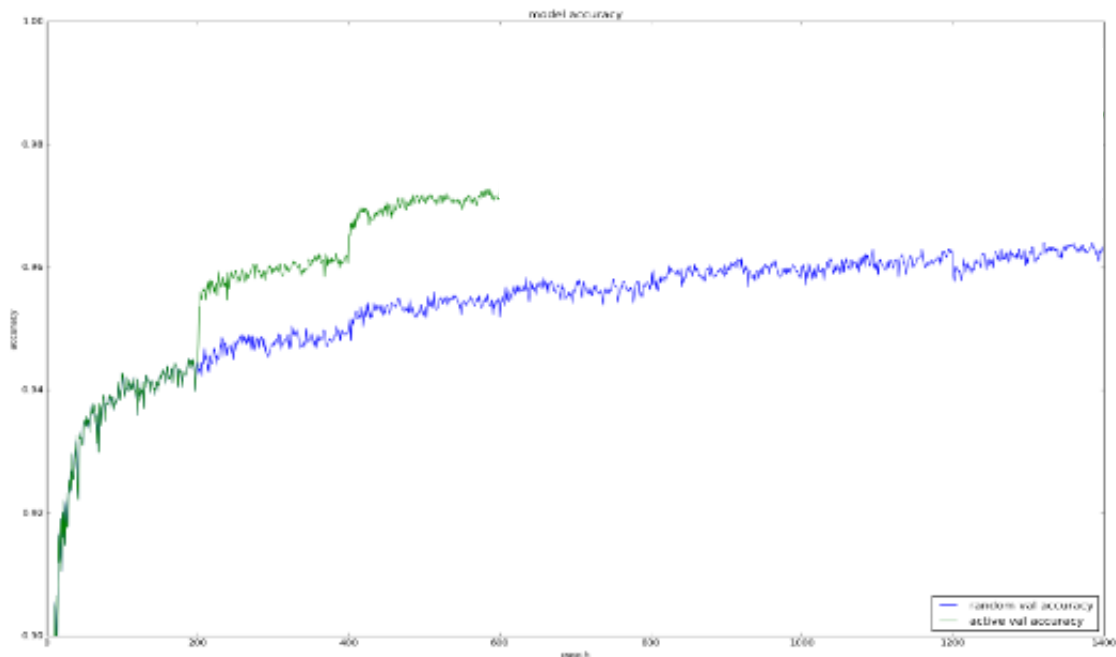
Classification results after two active learning cycles with an entropy policy.
Random baseline (blue) versus active strategy (green).

Classification Results



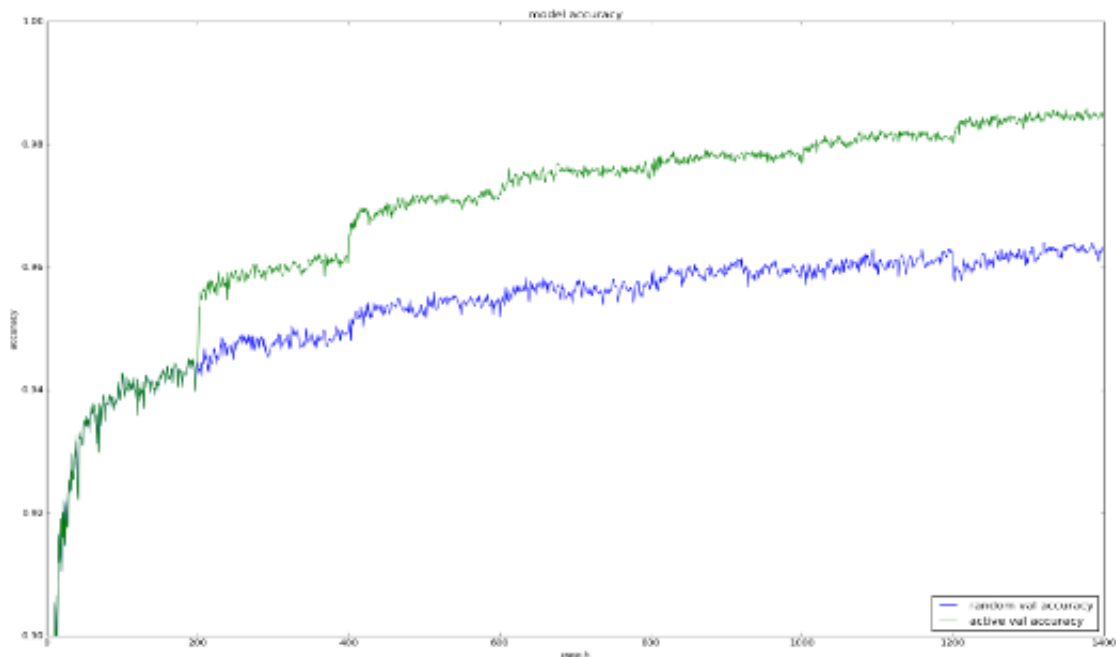
Classification results after two active learning cycles with an entropy policy.
Random baseline (blue) versus active strategy (green).

Classification Results



Classification results after six active learning cycles with an entropy policy.
Random baseline (blue) versus active strategy (green).

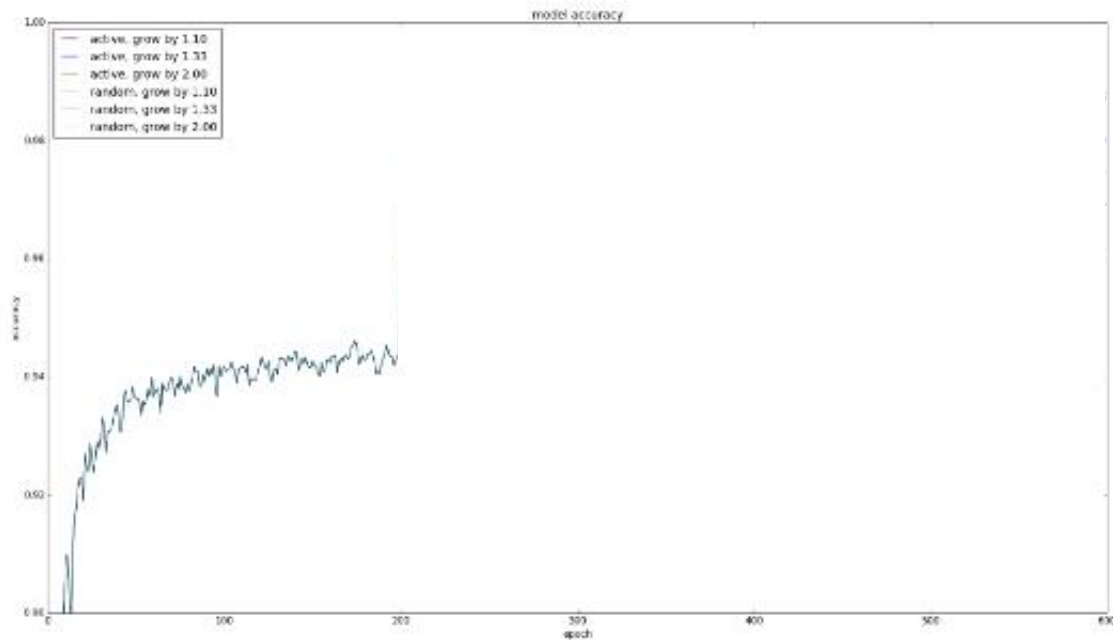
Classification Results



Classification results after six active learning cycles with an entropy policy.
Random baseline (blue) versus active strategy (green).

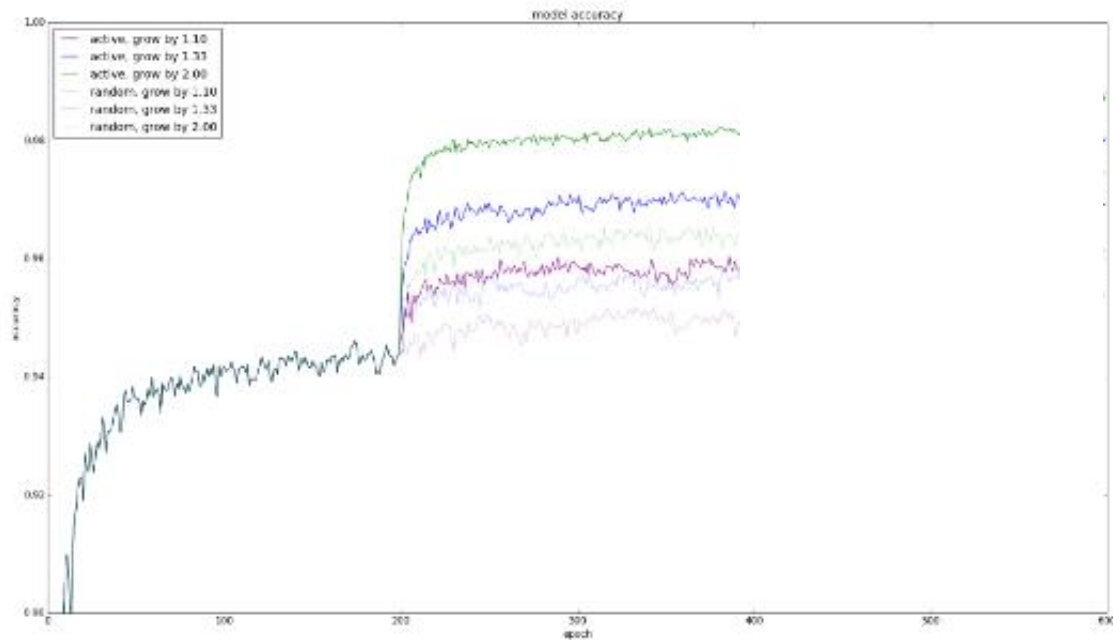
[Lesnikowski,
Farabet, 2017]

Classification Results



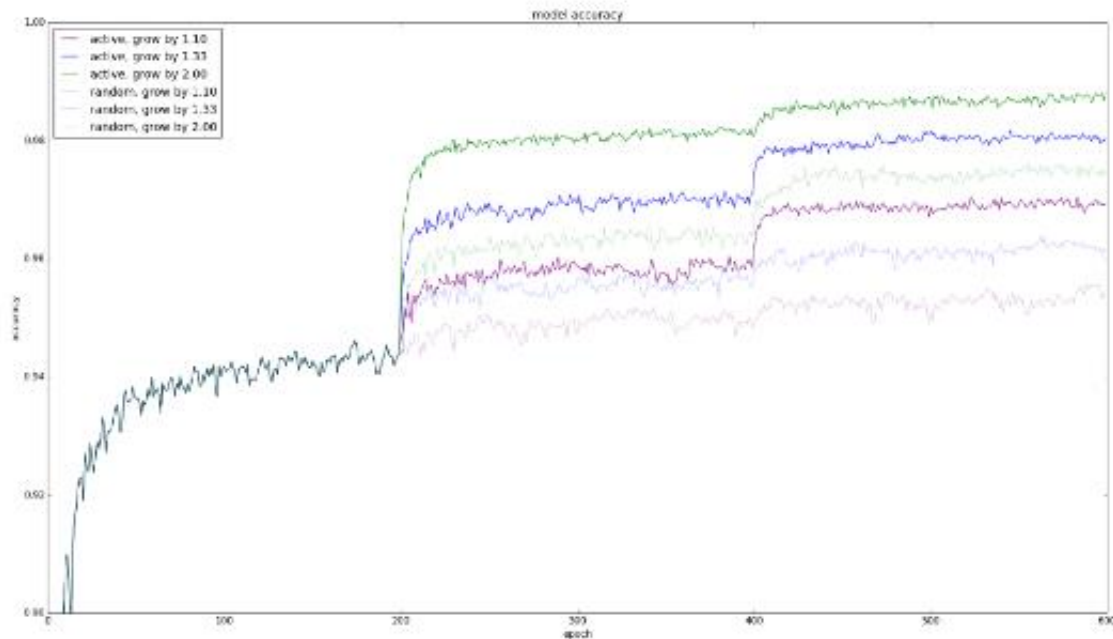
The effect of varying the growth parameter in active learning strategies.

Classification Results



The effect of varying the growth parameter in active learning strategies.
Adding 10% (purple), 33% (blue) and 100% (green).

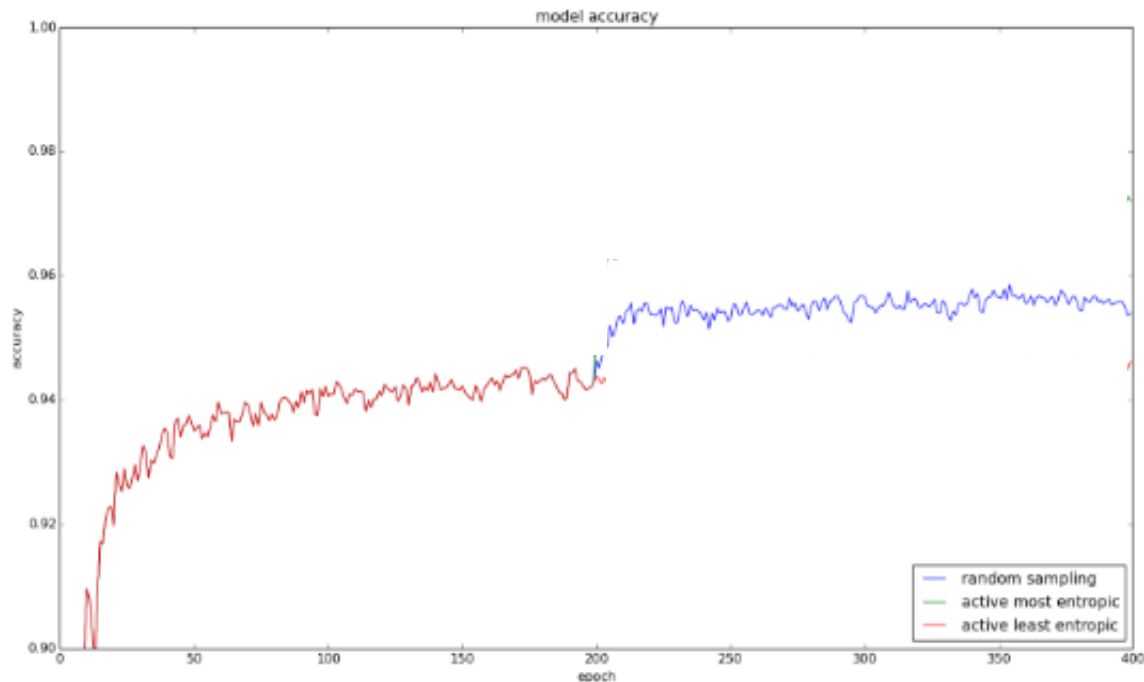
Classification Results



The effect of varying the growth parameter in active learning strategies.
Adding 10% (purple), 33% (blue) and 100% (green).

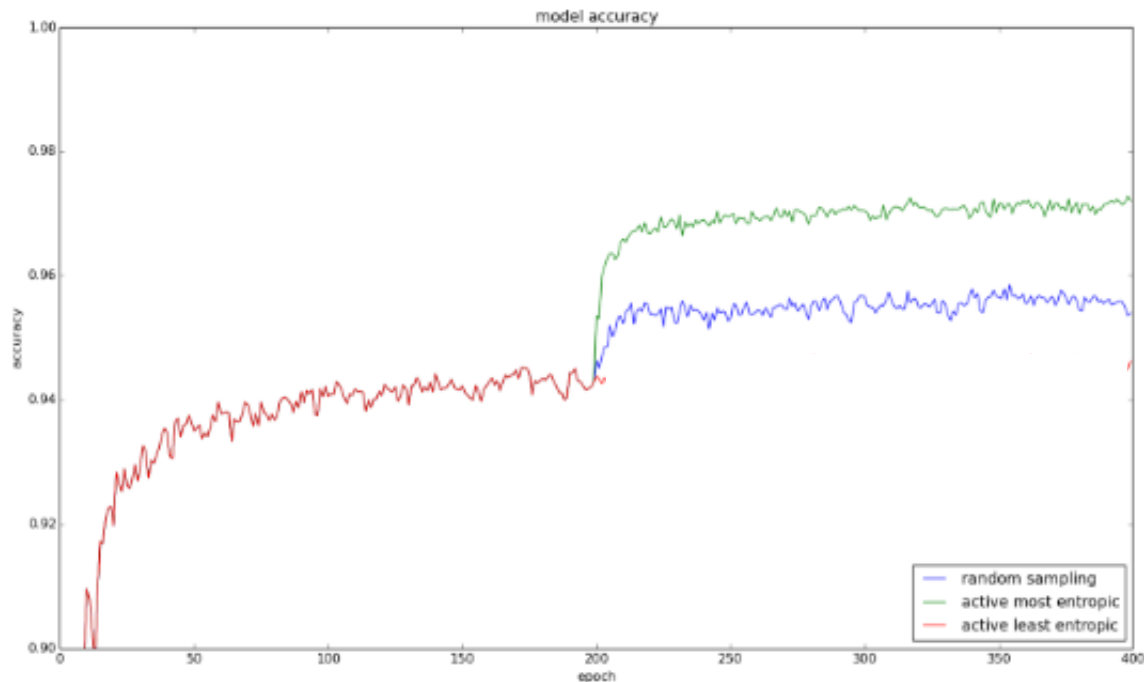
[Lesnikowski,
Farabet, 2017]

Classification Results



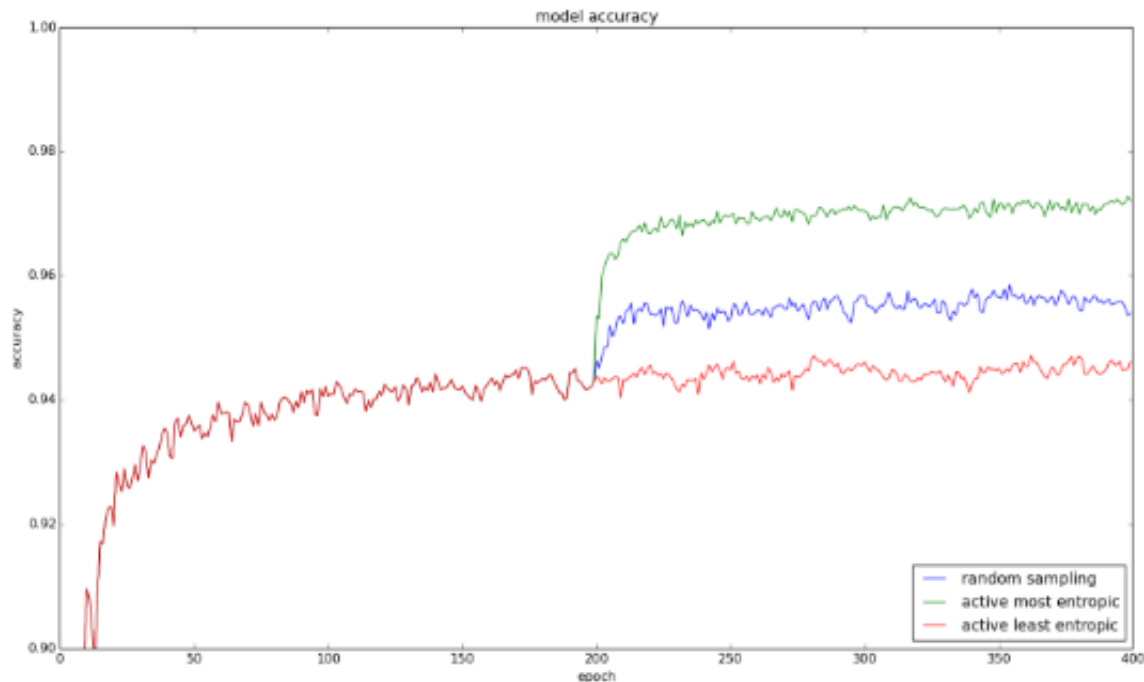
Sampling the least uncertain images (red) versus the most uncertain (green)
The random baseline is in blue.

Classification Results



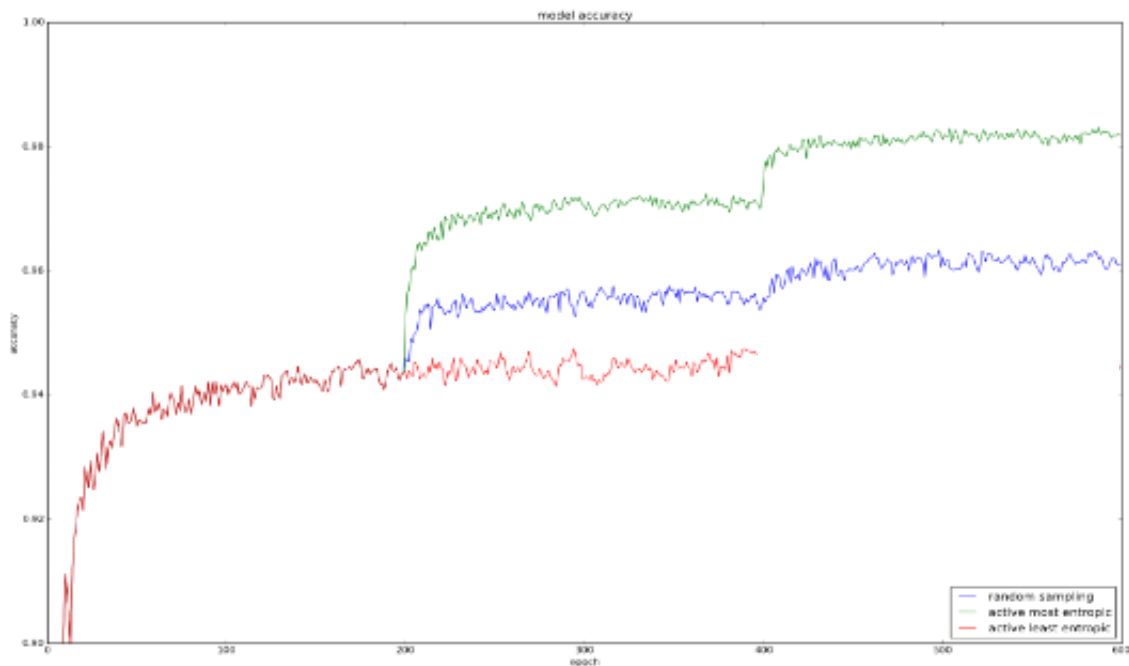
Sampling the least uncertain images (red) versus the most uncertain (green)
The random baseline is in blue.

Classification Results



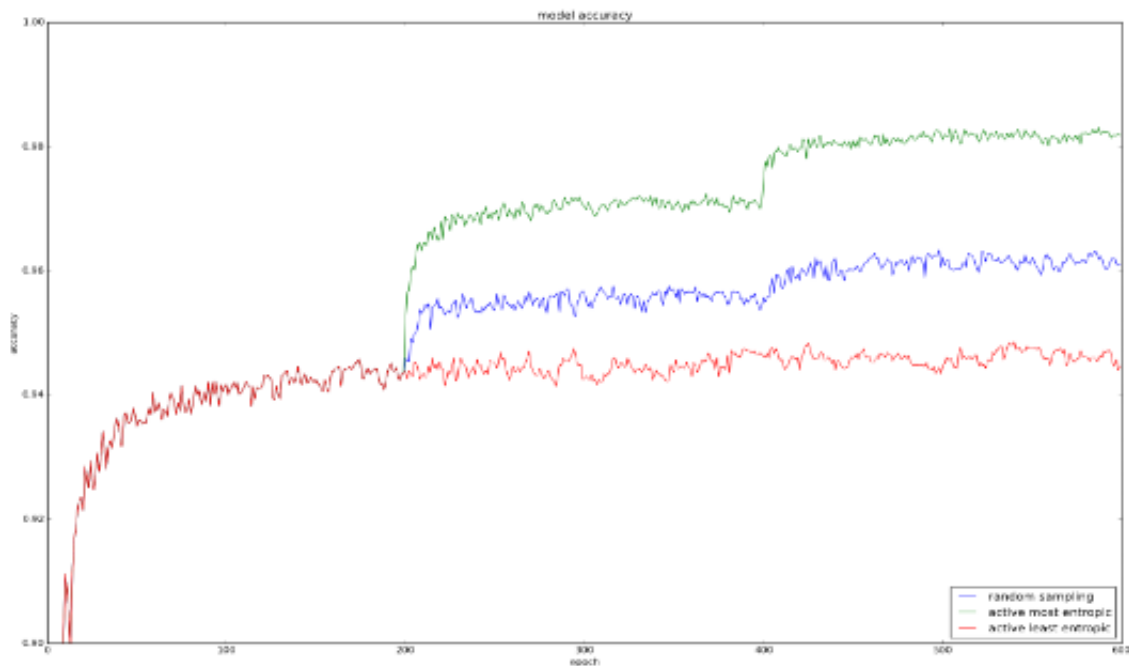
Sampling the least uncertain images (red) versus the most uncertain (green)
The random baseline is in blue.

Classification Results



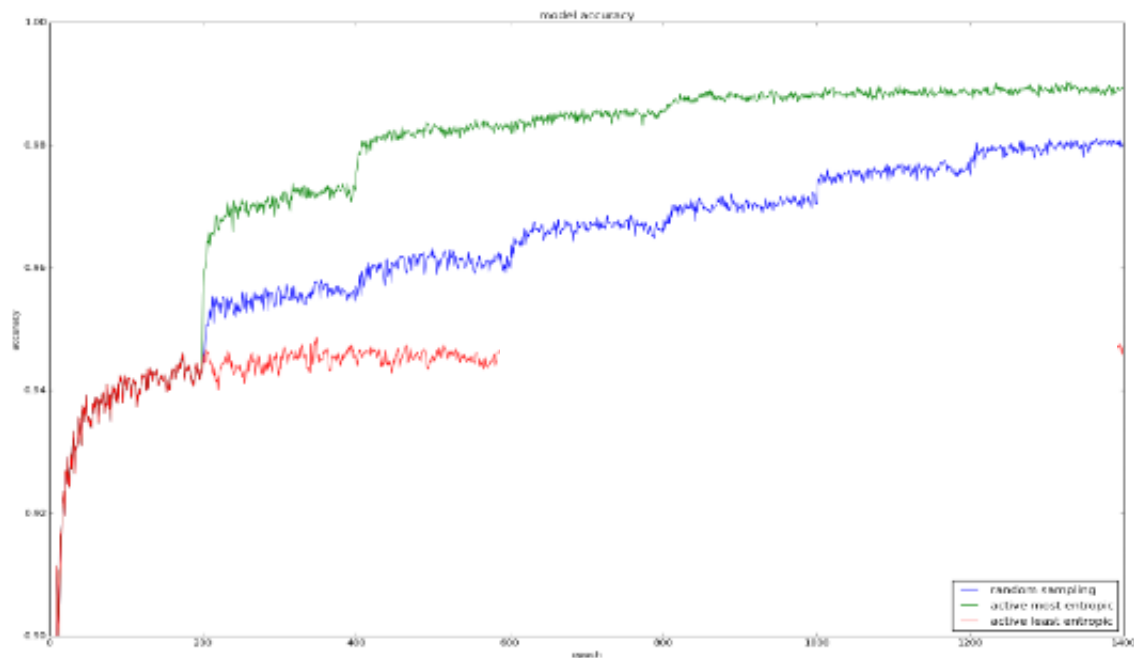
Sampling the least uncertain images (red) versus the most uncertain (green)
The random baseline is in blue. Two active learning loops.

Classification Results



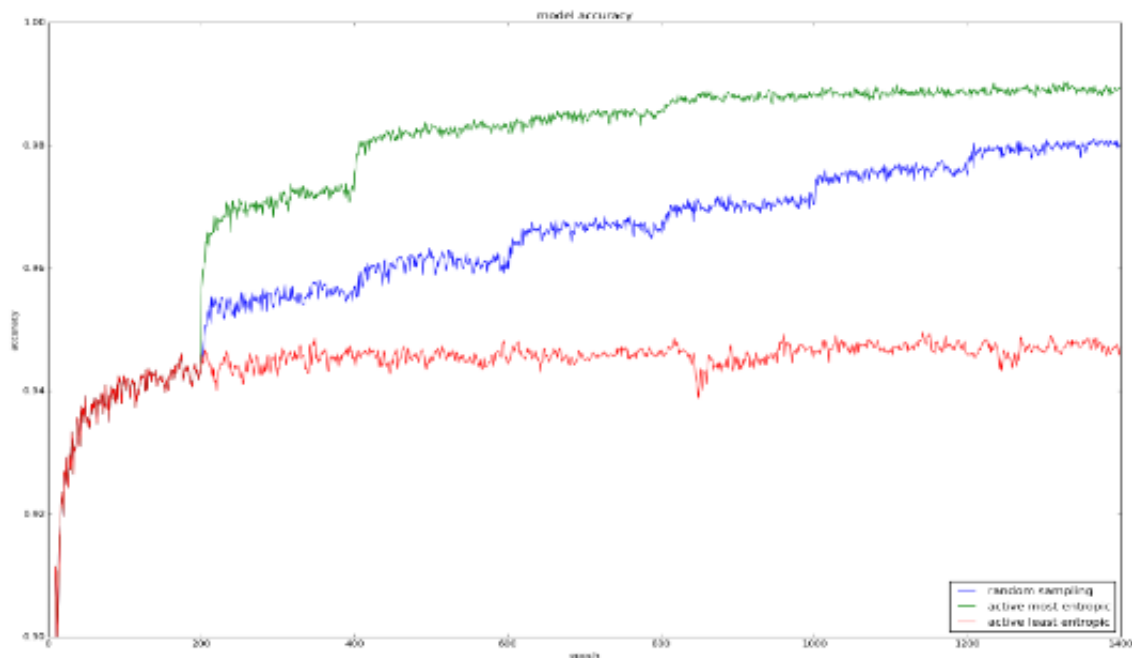
Sampling the least uncertain images (red) versus the most uncertain (green)
The random baseline is in blue. Two active learning loops.

Classification Results



Sampling the least uncertain images (red) versus the most uncertain (green)
The random baseline is in blue. **Six** active learning loops.

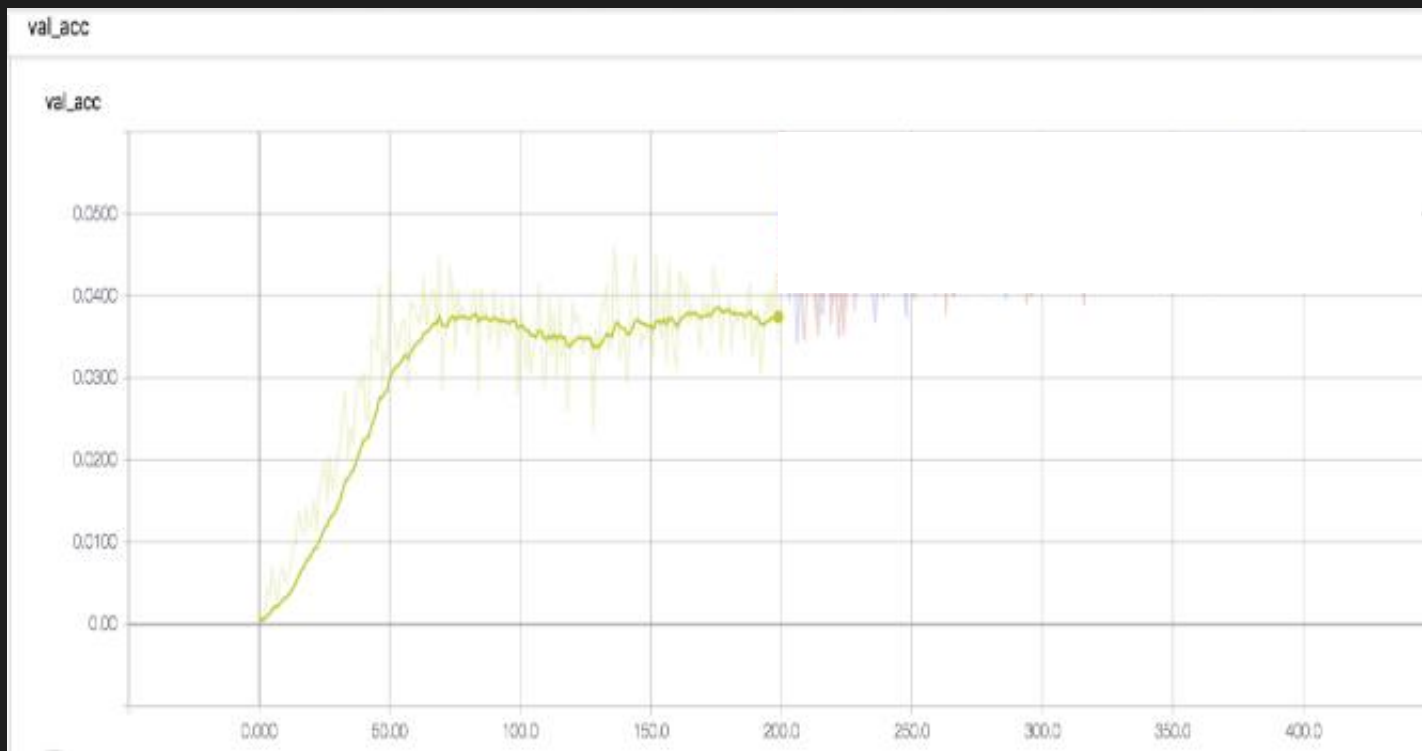
Classification Results



Sampling the least uncertain images (red) versus the most uncertain (green)
The random baseline is in blue. Six active learning loops.

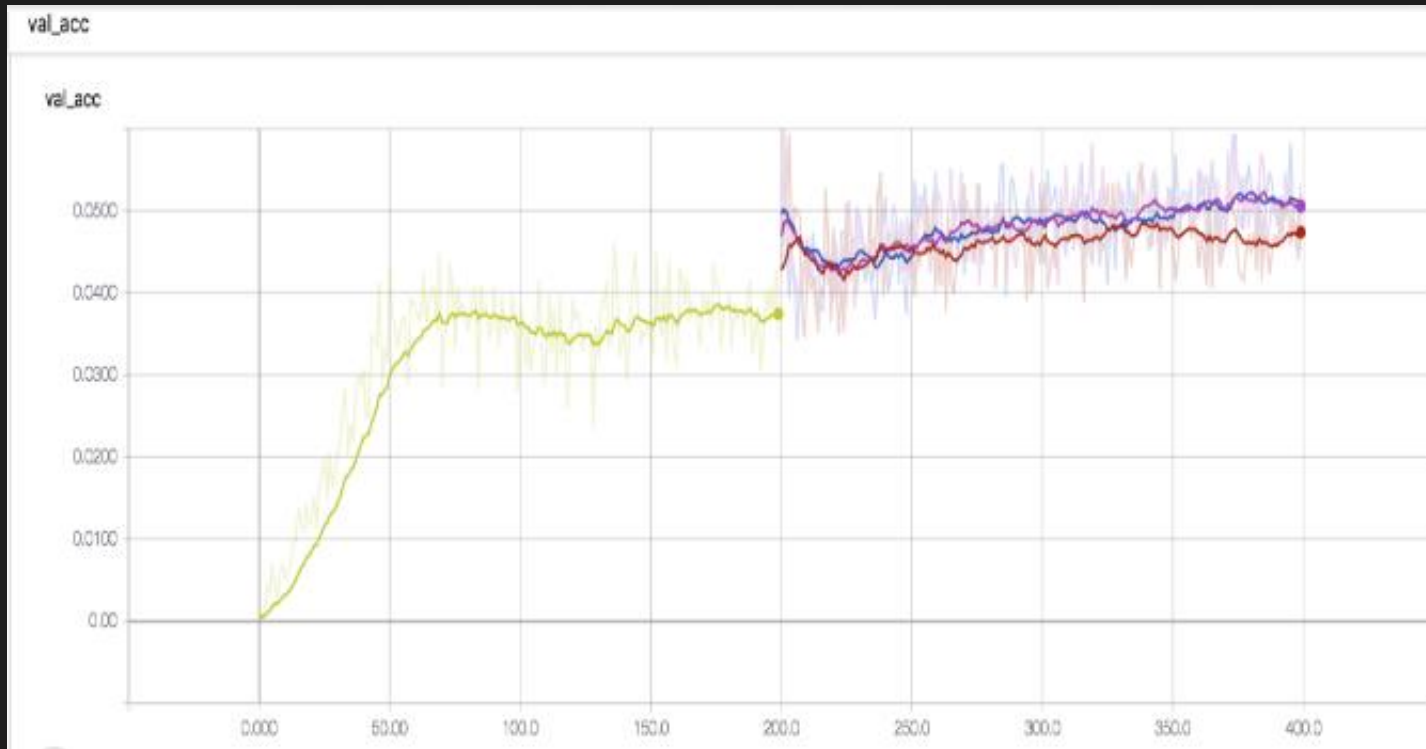
[Lesnikowski,
Farabet, 2017]

Scalability



Classification on ImageNet after one active learning cycle with a margin policy.
Random baseline (red) and two runs of the active strategy (blue and purple).

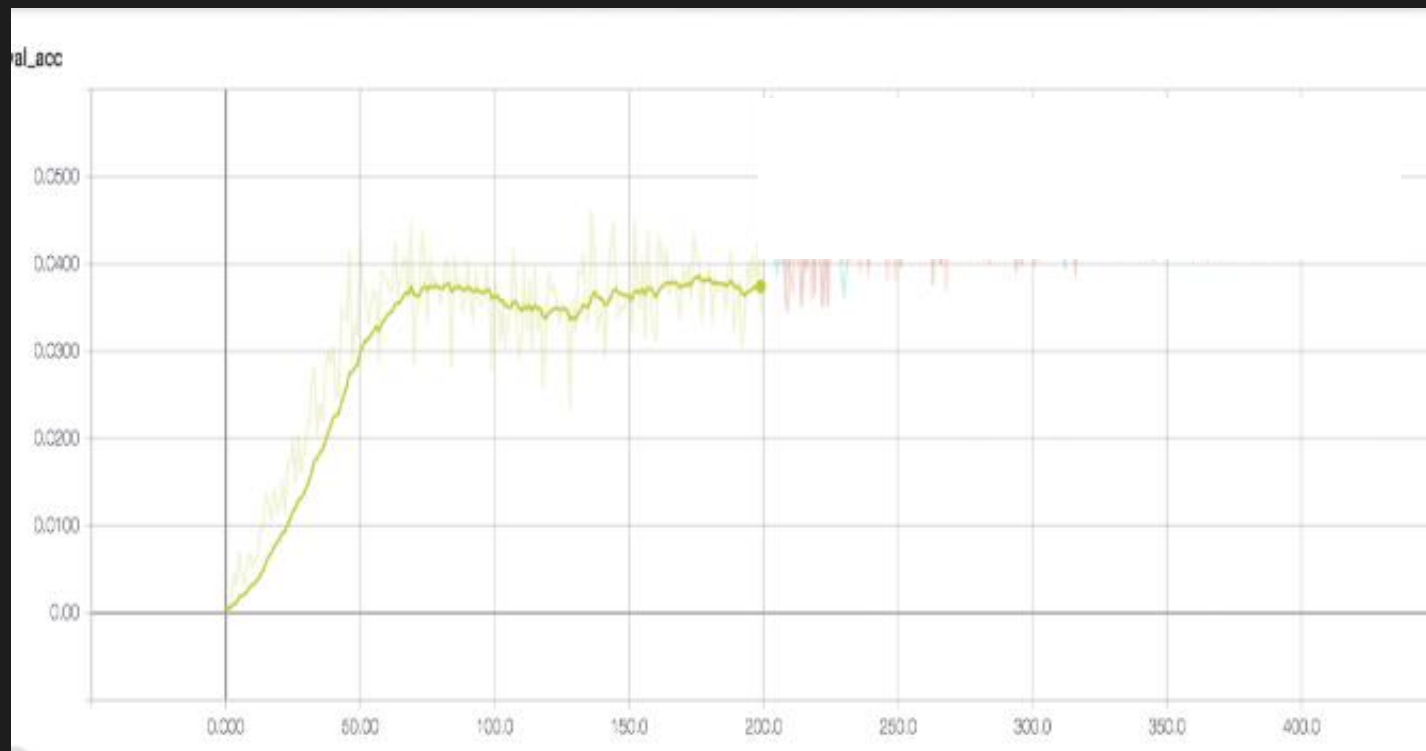
Scalability



Classification on ImageNet after one active learning cycle with a margin policy.
Random baseline (red) and two runs of the active strategy (blue and purple).

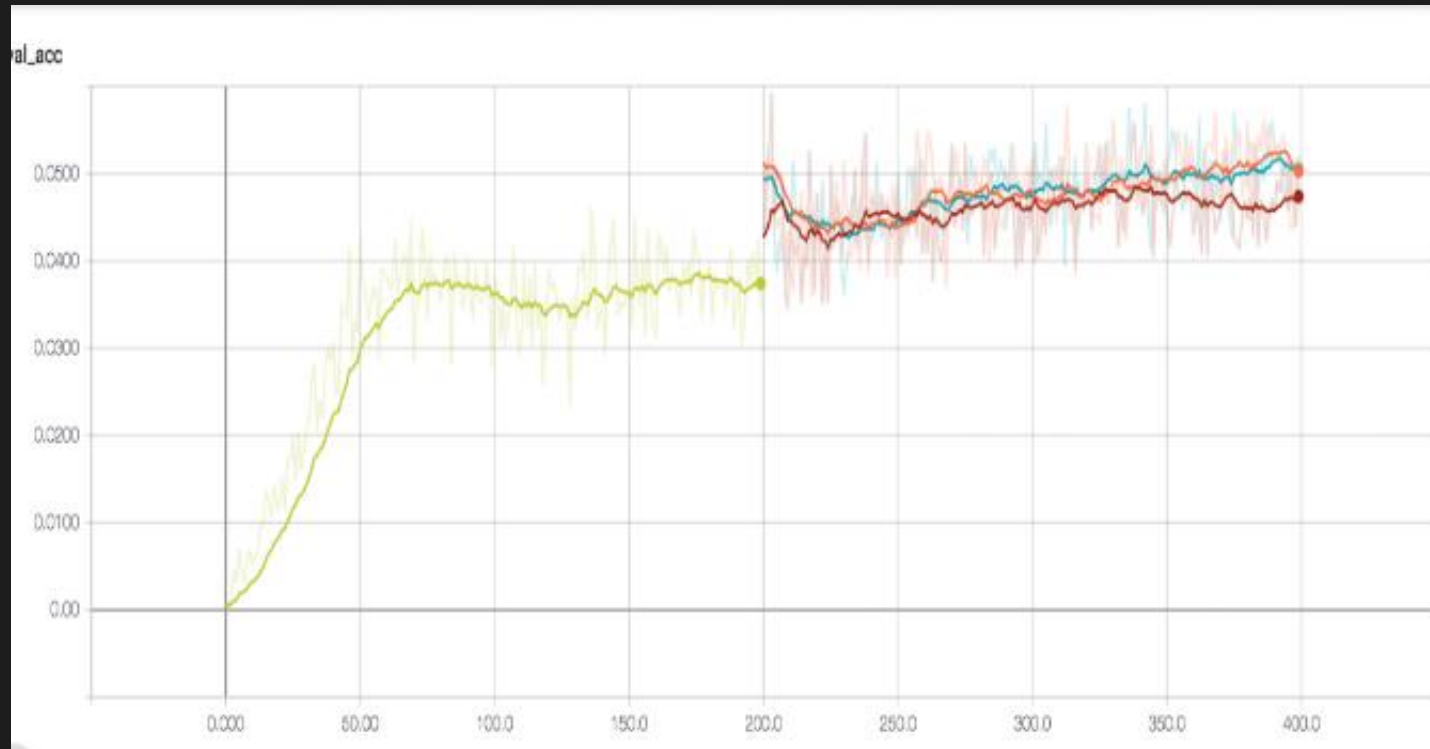
[Lesnikowski,
Schoffier,
Farabet, 2017]

Scalability



Classification on ImageNet after one active learning cycle with an entropy policy.
Random baseline (red) and two runs of the active strategy (blue and orange).

Scalability



Classification on ImageNet after one active learning cycle with an entropy policy. Random baseline (red) and two runs of the active strategy (blue and orange).

[Lesnikowski, Farabet, 2017]

Conclusions

Conclusions

- * Deep active learning **works**
- * Gives **significant efficiency gains** in time and money
- * Exciting work in progress and **more to come!**

Thanks!



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Shiyu Liang, NVIDIA

Qs, As and Discussion

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Thank you!

Qs, As and Discussion



Thank you!

