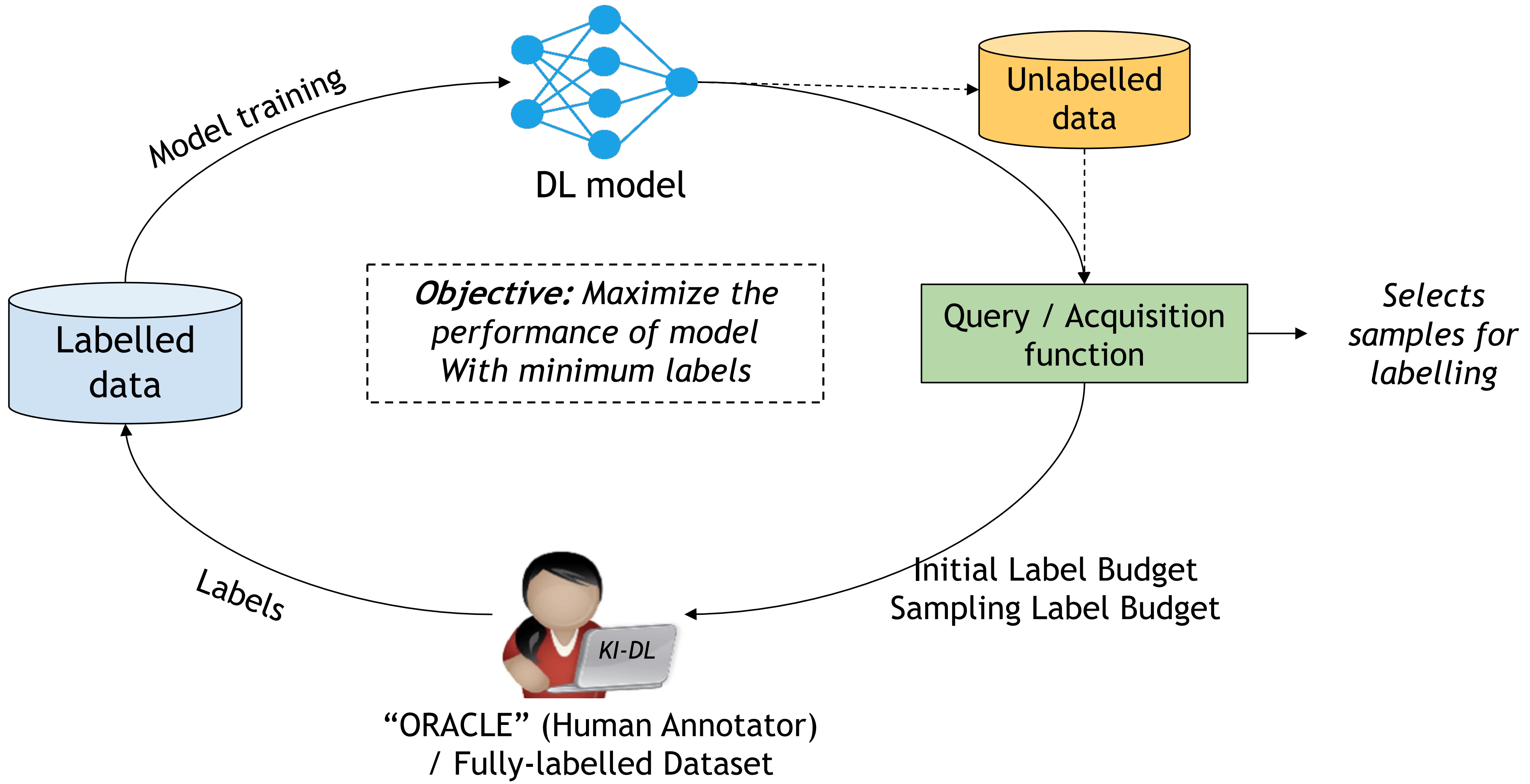
Final Event| March 09, 2023

Active Learning for Semantic Segmentation in Realistic Driving Scenarios

Joshua Niemeijer, Sudhanshu Mittal

KI DELTA LEARNING
Scalable AI for Automated Driving

Deep Active Learning: Settings and Objective

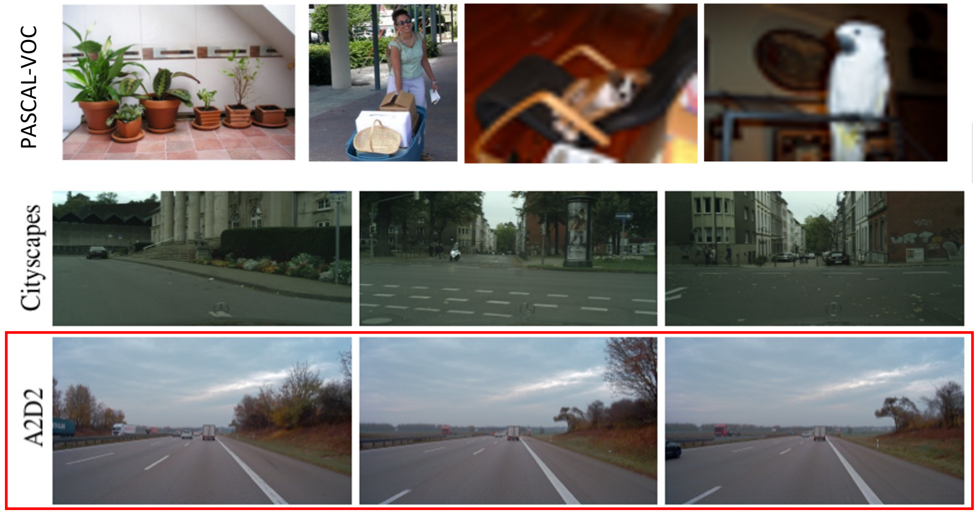


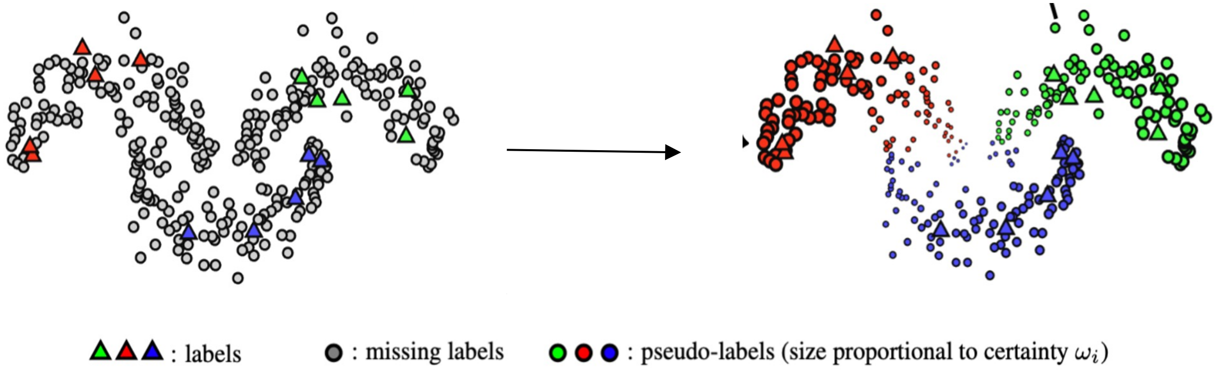
Active Learning for Segmentation for Driving Datasets

Why AL for Semantic Segmentation?

- Images easy to collect
  - ➢ lots of unlabeled video data
- Annotation is expensive
  - ➢ Pixel-wise labeling

Deep Active Learning: Research Questions





- Current benchmarks focus on diverse data
- Real data is very redundant
- ➢ ***To study AL methods for different distributions w.r.t. redundancy in the dataset.***

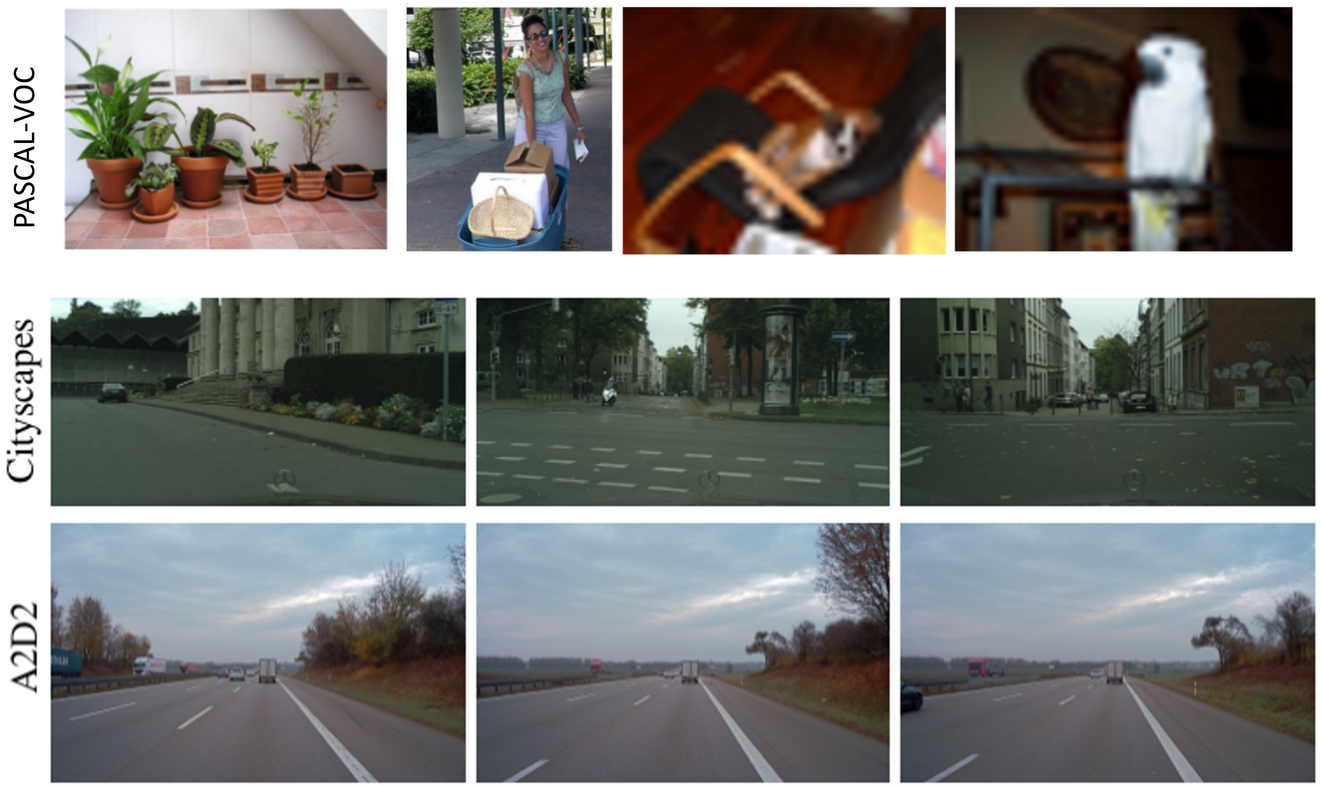
- Integration of semi-supervised learning with AL is high effective for image classification
- ➢ ***To study AL methods with the integration of semi-supervised learning.***

Experiments:

Datasets & Methods

Experiment Settings: Datasets

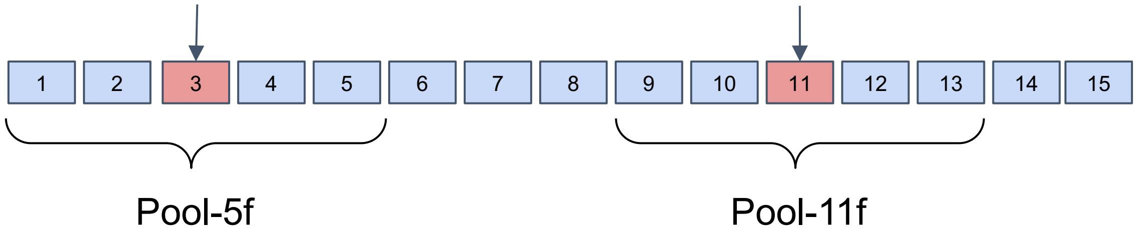
- Datasets (increasing redundancy ↓)
  - PASCAL-VOC
  - Cityscapes
  - A2D2
    - A2D2: Pool-0f
    - A2D2: Pool-5f
    - A2D2: Pool-11f
    - A2D2: Pool-21f
    - A2D2: Pool-Aug



Experiment Settings: Datasets

- Datasets (increasing redundancy ↓)
  - PASCAL-VOC
  - Cityscapes
  - A2D2
    - A2D2: Pool-0f
    - A2D2: Pool-5f
    - A2D2: Pool-11f
    - A2D2: Pool-21f
    - A2D2: Pool-Aug

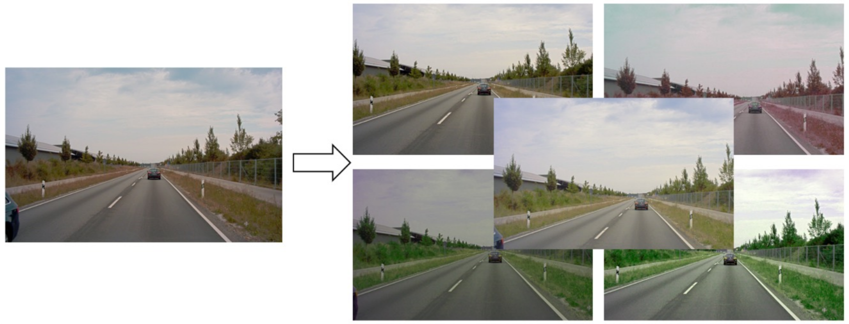
- Datasets with different levels of redundancy
- Size: ~3K sampled from original A2D2 dataset
- Pool-Xf, where X=0,5,11,21 consecutive frames sampled randomly



Experiment Settings: Datasets

- Datasets (increasing redundancy ↓)
  - PASCAL-VOC
  - Cityscapes
  - A2D2
    - A2D2: Pool-0f
    - A2D2: Pool-5f
    - A2D2: Pool-11f
    - A2D2: Pool-21f
    - A2D2: Pool-Aug

- Datasets with different levels of redundancy
- Size: ~3K sampled from original A2D2 dataset
- Pool-Xf, where X=0,5,11,21 consecutive frames sampled randomly
- Pool-Aug: 5 augmentations from each randomly sampled frame



Active Learning Acquisition Methods

Single-sample acquisition method

- ➢ Based on per sample objective

- Uncertainty-based
  - Entropy
  - Ensemble-based functions
  - EqualAL/ Consistency
  - BALD
  - Margin
  - Learning Loss

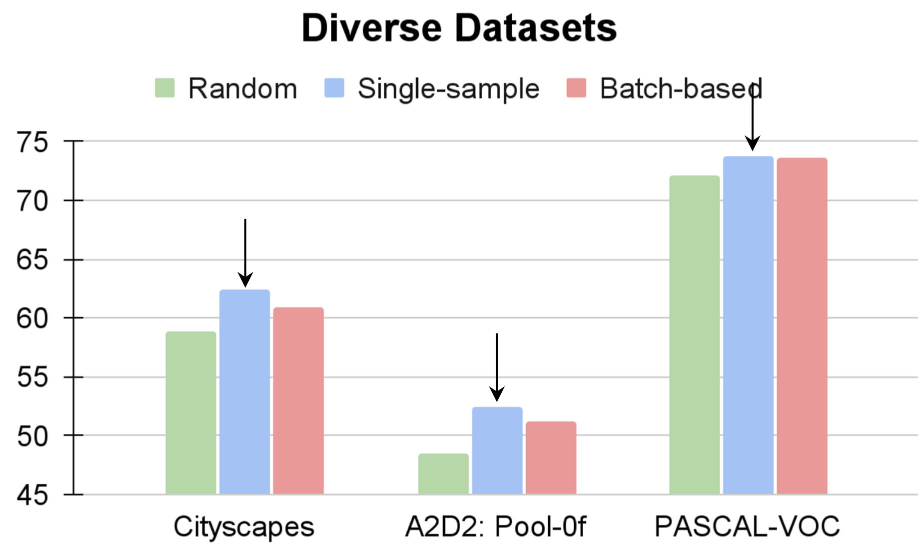
Batch-based acquisition method

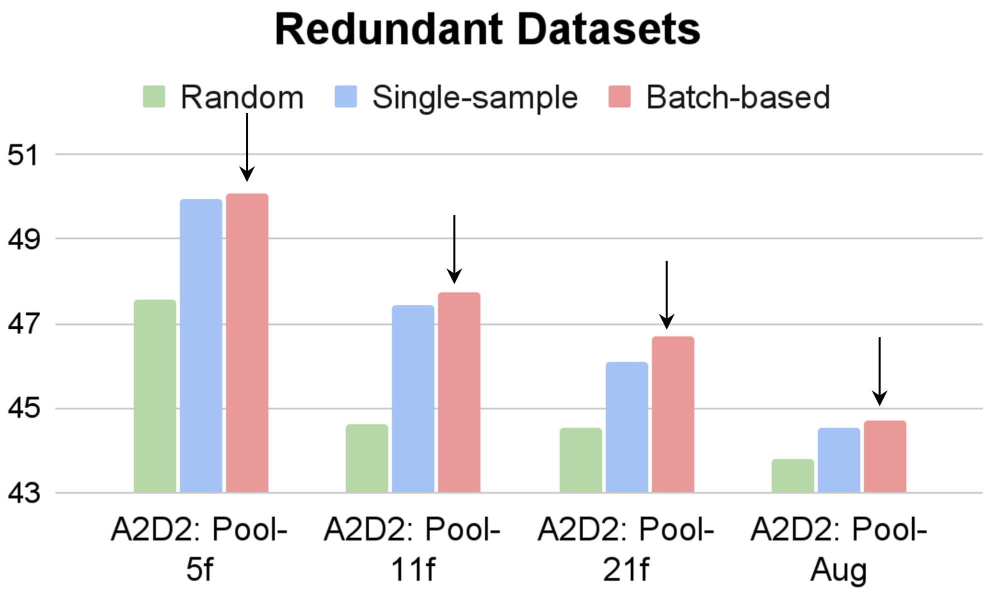
- ➢ Based on batch cumulative objective

- Coreset selection
  - K-center selection
- Clustering
  - K-means

Results

Single-sample vs Batch-based Active Learning: Results



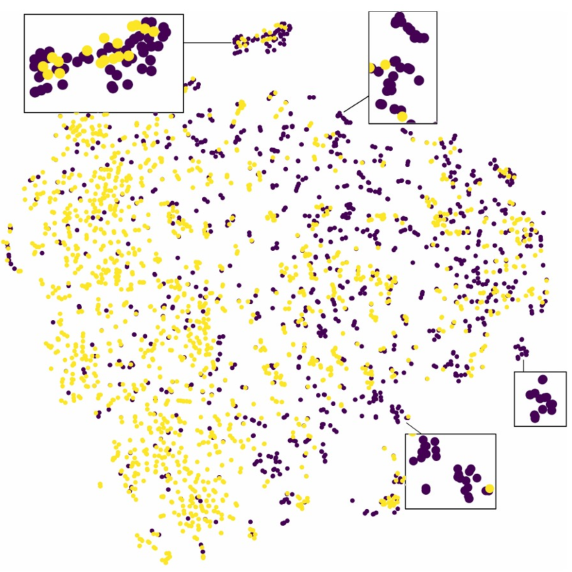


- Single-sample acquisition methods perform better on diverse datasets.
- Batch-based acquisition methods perform better on redundant datasets.

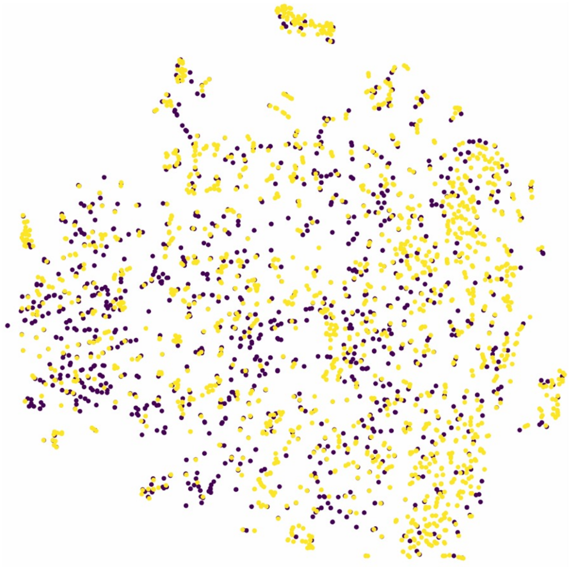
Single-sample vs Batch-based Active Learning: Analysis

- TSNE on A2D2: Pool-11f
  - *Redundant dataset*

- Single-sample performs worse on redundant datasets
  - Due to ***mode collapse***

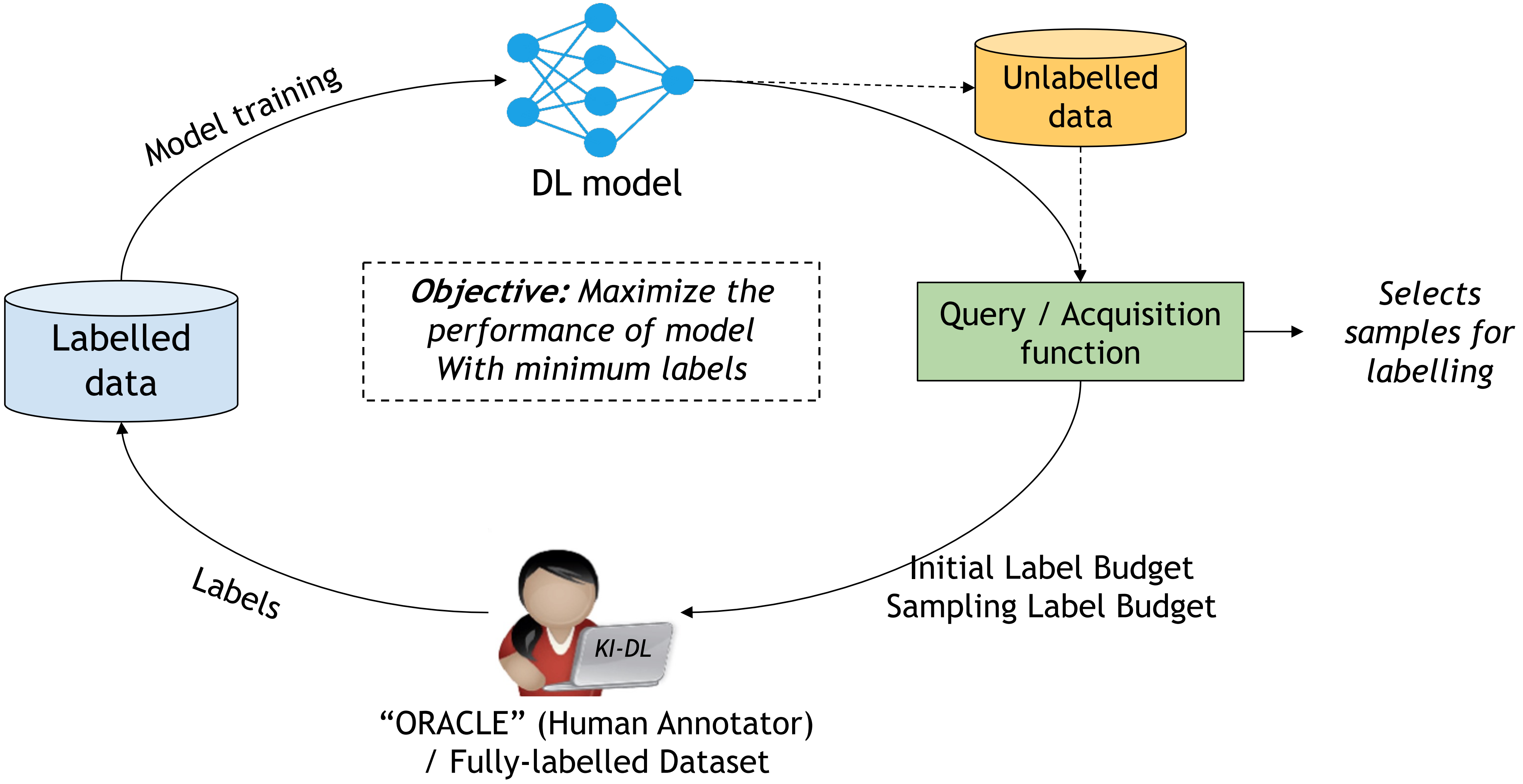


Single-sample Acquisition

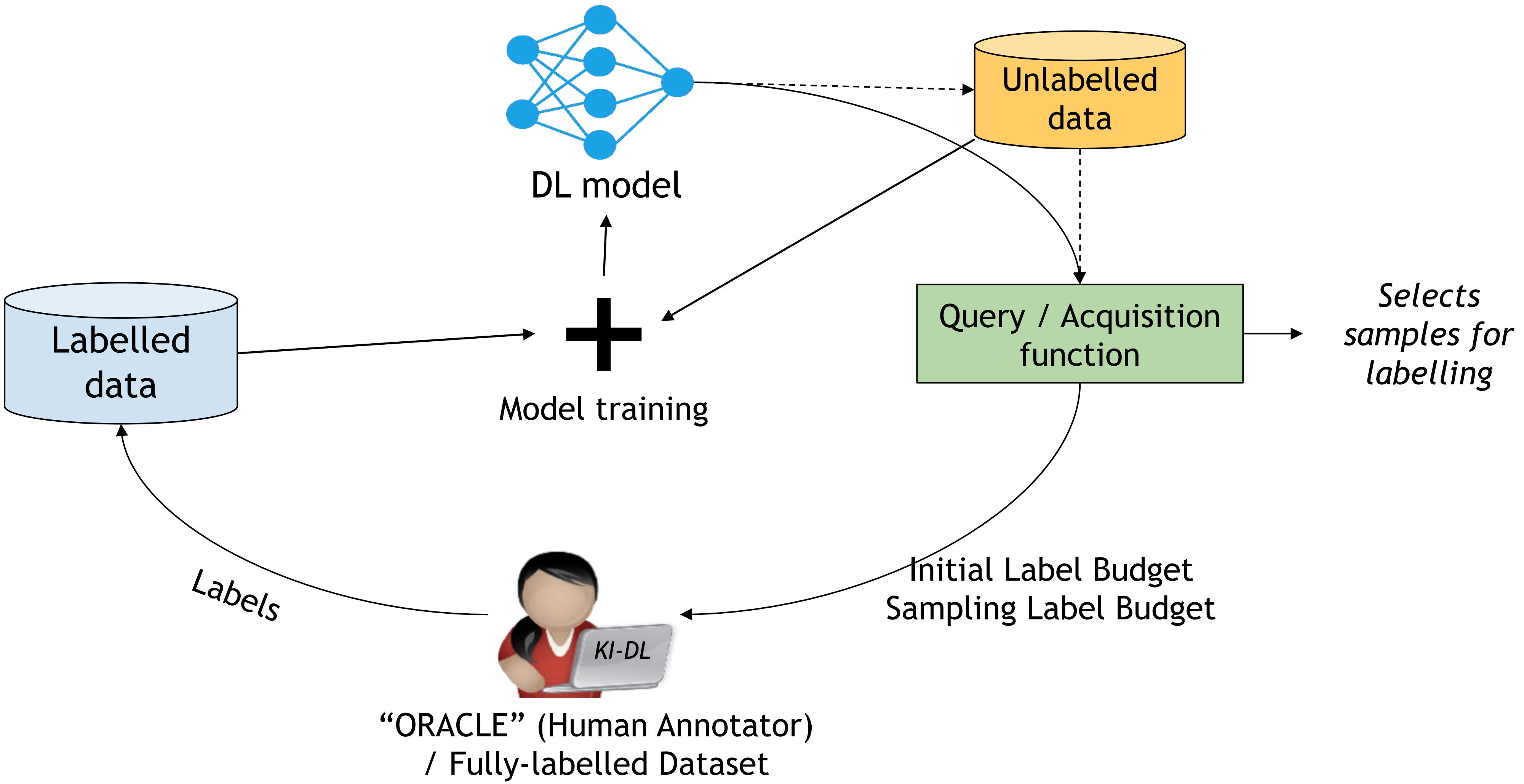


Batch-based acquisition

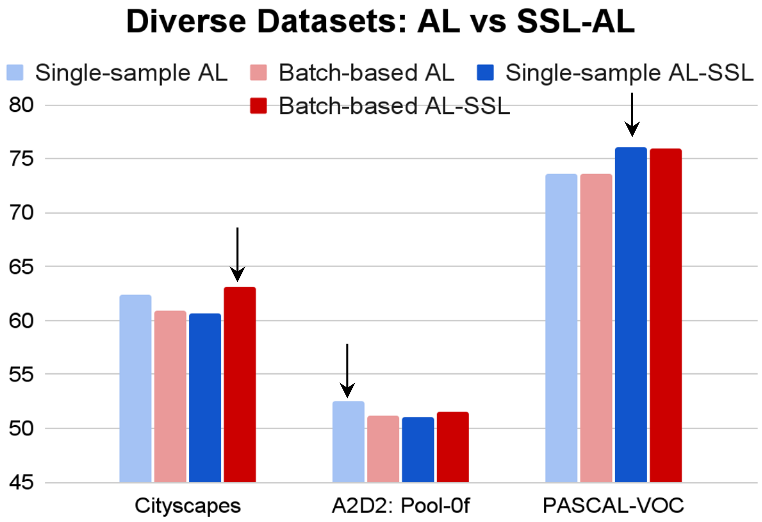
Deep Active Learning: Supervised Setting

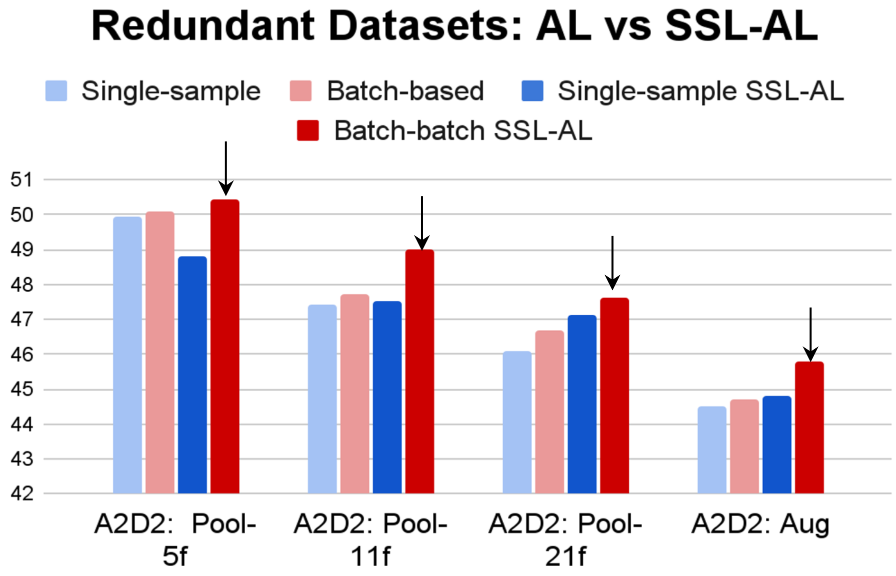


Deep Active Learning: Integration of Semi-supervised Learning



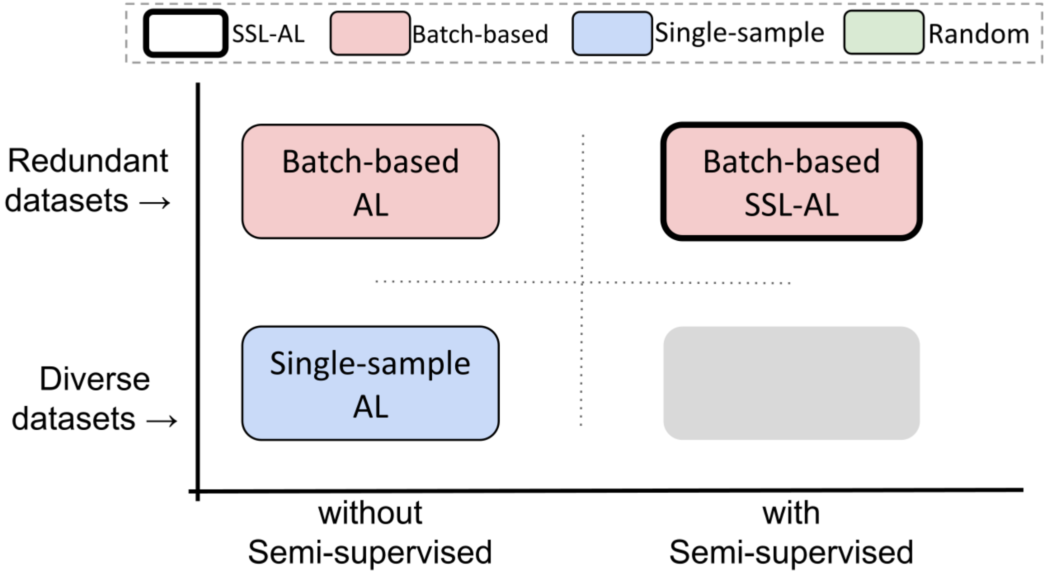
Integration of Semi-supervised Learning: Results





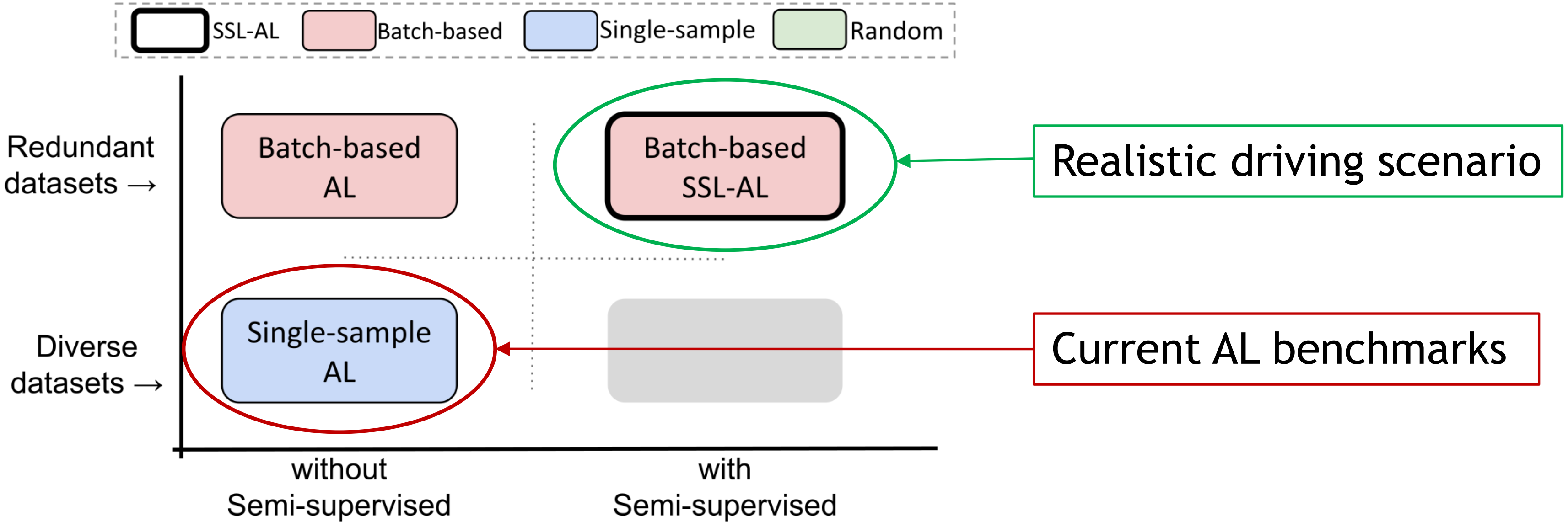
- SSL is especially effective for redundant datasets.
- Semi-supervised learning aligns well with the batch-based method (CoreSet).
  - *SSL cluster assumption is compatible with CoreSet objective.*

Results Overview



- Single-sample uncertainty-driven method → *diverse datasets*
- Batch-based diversity-driven method → *redundant datasets*
- SSL integrates well with batch-based method.

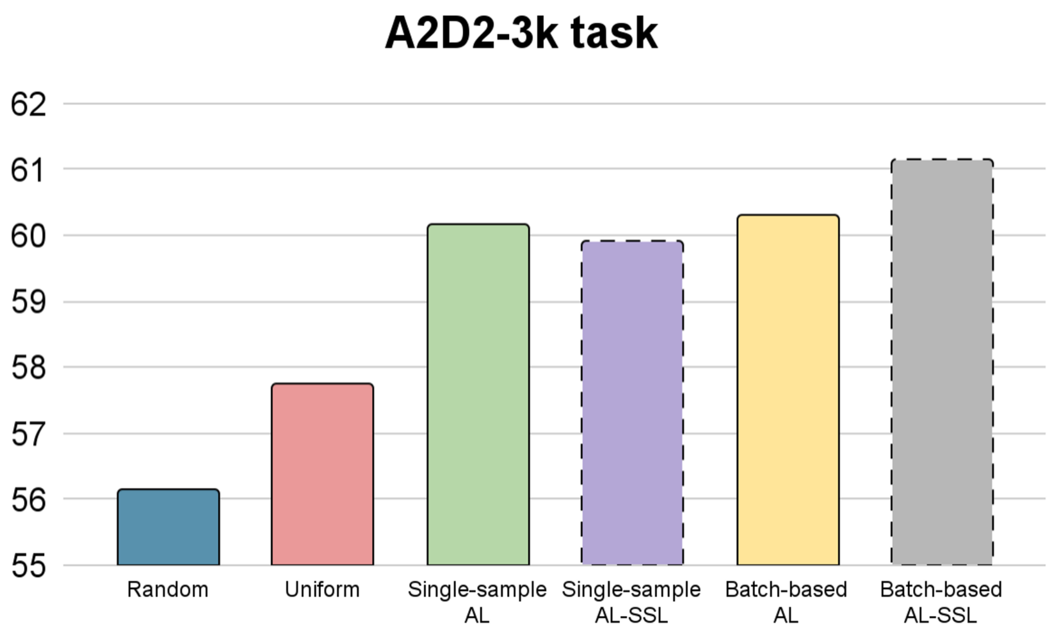
New Realistic A2D2-3k Task



- Current AL benchmarks for driving data are unrealistic.
- We propose a suitable task for realistic evaluation of driving datasets.

New Realistic A2D2-3k Task

Objective: To select 3K samples(~ Cityscapes size) from A2D2 dataset(~40K samples) to get best performance



- Uniform sampling is sub-optimal
- Batch-based acquisition with SSL works the best.

Conclusion

- Active Learning for Semantic Segmentation is vital.
- We provide some essentials for successful usage of AL methods based on
  - Data distribution
  - Acquisition functions
  - Integration of semi-supervised learning

Thank you!

KIDELTA LEARNING
Scalable AI for Automated Driving

Sudhanshu Mittal | Uni Freiburg

mittal@cs.uni-freiburg.de

Joshua Niemeijer | DLR

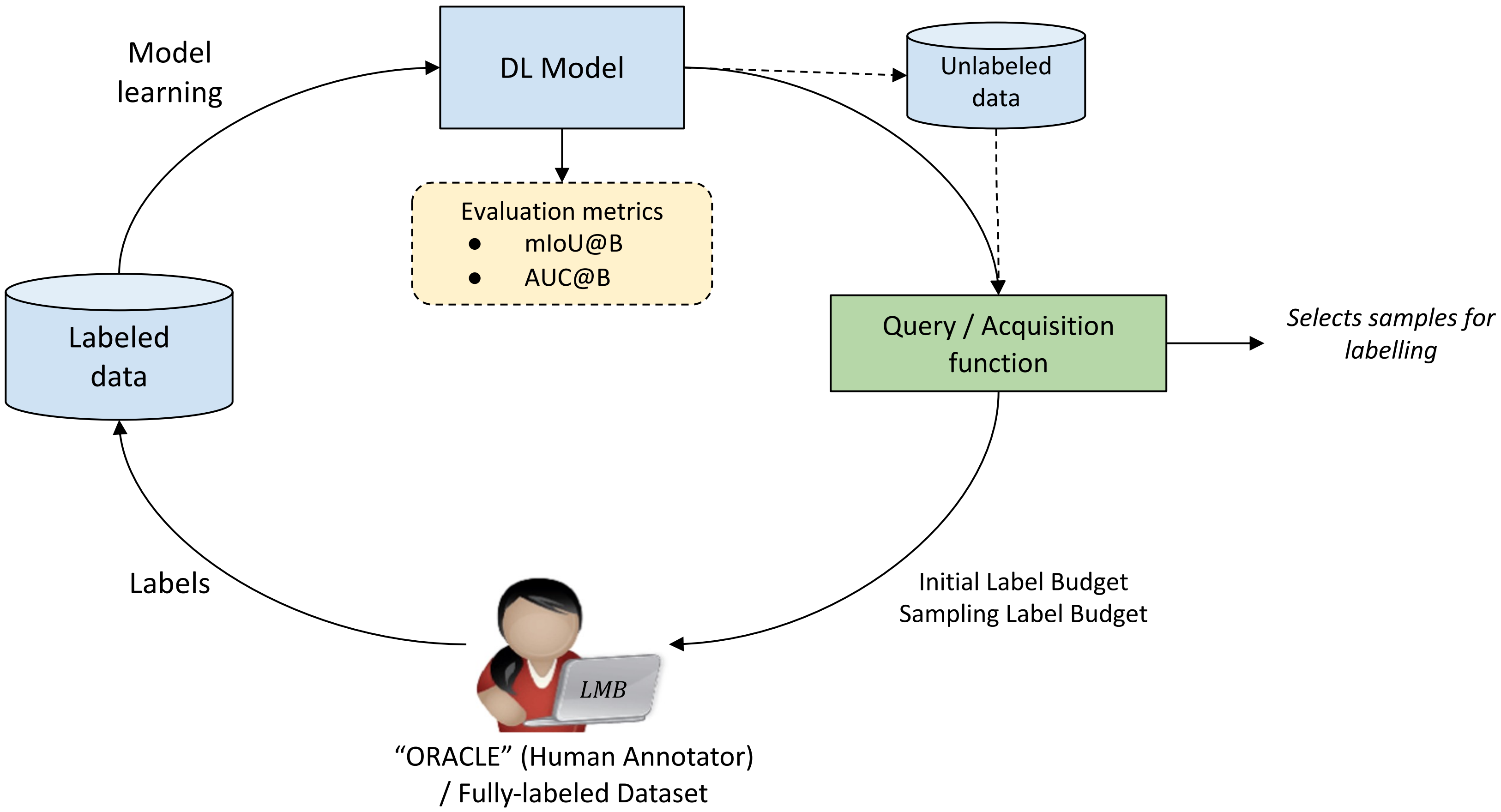
Joshua.Niemeijer@dlr.de

KI Delta Learning is a project of the KI Familie. It was initiated and developed by the VDA Leitinitiative autonomous and connected driving and is funded by the Federal Ministry for Economic Affairs and Climate Action.

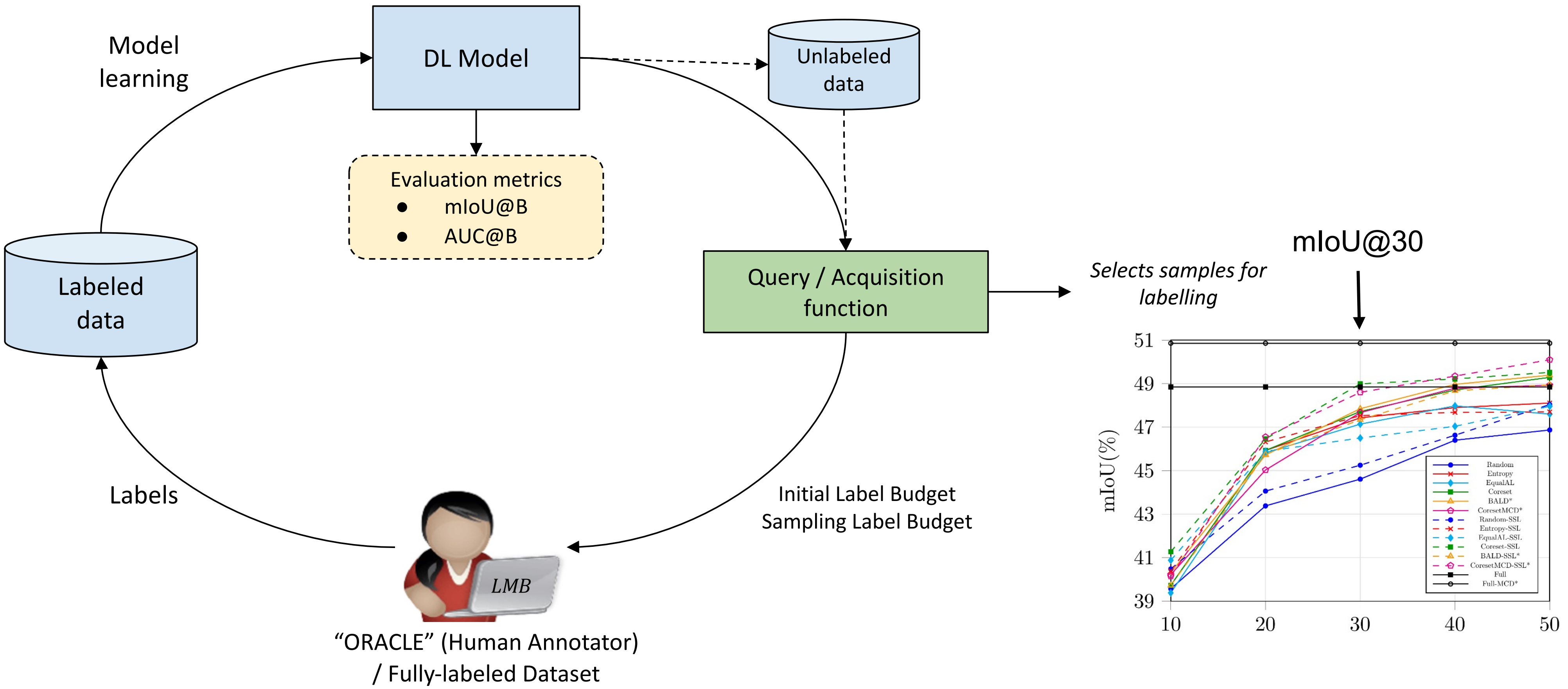
KI FAMILIE

Supported by:
Federal Ministry for Economic Affairs and Climate Action
on the basis of a decision by the German Bundestag

Deep Active Learning: Evaluation



Deep Active Learning: Evaluation



Deep Active Learning: Evaluation