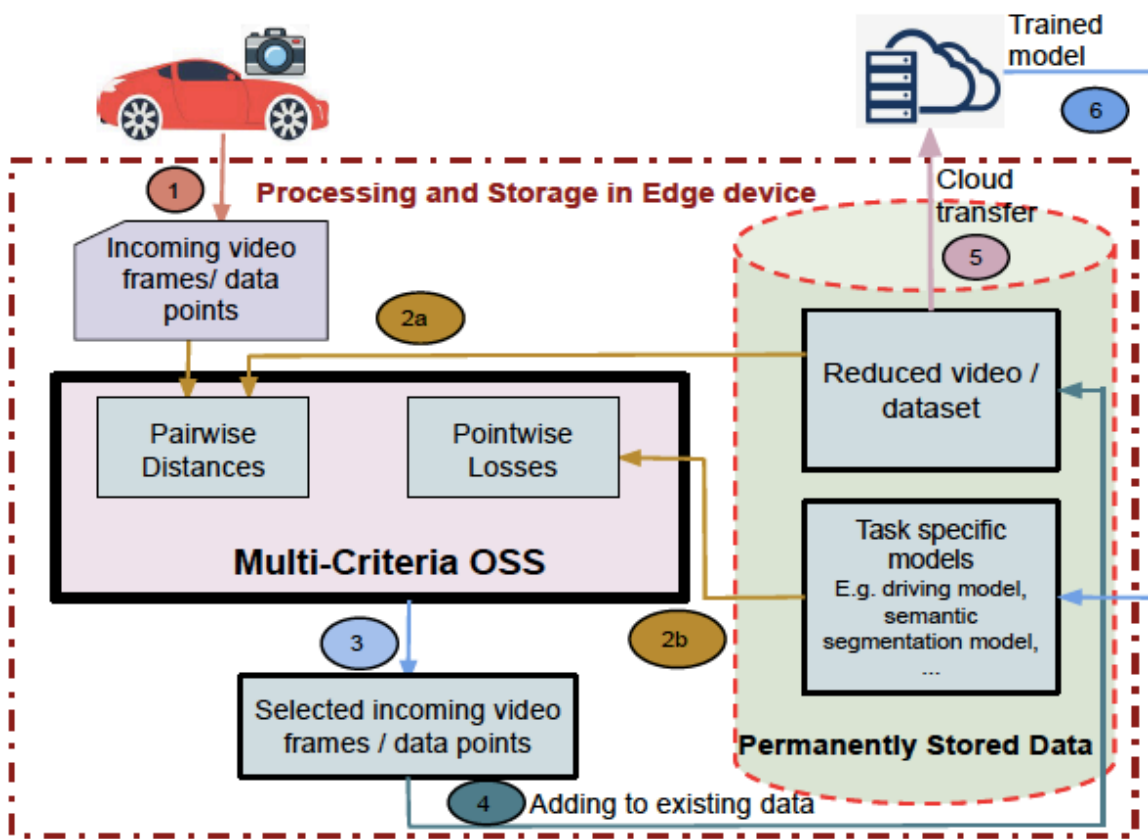


# TMCOSS: Thresholded Multi-Criteria Online Subset Selection for Data-Efficient Autonomous Driving

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## Setting



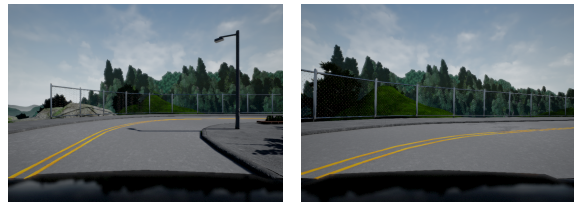
**Idea:** Developing a **thresholded multi-criteria online subset selection (TMCOSS)** algorithm that can select the most informative video frames.

## Aim

- Data-efficient training of autonomous driving systems.
- In the context of an edge-device deployment, **multi-criteria online video frame subset selection** is an appropriate technique for developing frameworks to remove redundant data.



**Straight road frames**  
**REDUNDANT**



**Turning point frames**  
**INFORMATIVE**

## Challenge

Subset selection on autonomous driving is challenging since failing to select informative frames can lead to abysmal performance like incomplete episodes while driving at turns.

Baseline Methods (100:20 compression)	Train One-Turn	Test One-turn
Uniform Skip	3/10	5/10
OSS[1]	7/10	6/10

## TMCOSS: Thresholded Multi-Criteria OSS

$$\min_{z_{ij}^o, z_{ij}^n} \mathcal{G}(z_{ij}^o, z_{ij}^n) s.t. \sum_{j=1}^{|R_i|} z_{i,j}^o + \sum_{j=1}^m z_{i,j}^n = 1; z_{i,j}^o, z_{i,j}^n \in [0,1]; \sum_{j=1}^m \|[z_{1,j}^n \dots z_{m,j}^n]\|_p \leq frac * m$$

Objective function      Representative      Domain      Compression Ratio

Constraints

$$\mathcal{G}(z_{ij}^o, z_{ij}^n) = \rho (\sum_{i=1}^m \sum_{j=1}^{|R_i|} z_{ij}^o d_{ij}^o(t) + \sum_{i,j=1}^m z_{ij}^n d_{ij}^n(t)) - (1 - \rho) (\sum_{j=1}^{|R_i|} S_j^o * L_j^o + \sum_{j=1}^m S_j^n * L_j^n)$$

Pairwise Dissimilarity      Pointwise Loss

$$where, S_j^o = \frac{1}{\epsilon} \min(\epsilon, \sum_{i=1}^m z_{ij}^o), S_j^n = \frac{1}{\epsilon} \min(\epsilon, \sum_{i=1}^m z_{ij}^n)$$

Representative power of element j thresholded by  $\epsilon$

## Variants of TMCOSS

Driving requires several cues/affordances for taking the next move. We use Conditional Affordance Learning [3] model as the driving model. In order to complete an episode involving turns, **relative angle is a vital signal**. We introduce 2 variants of TMCOSS:

### TMCOSS-TL

Total Loss of affordances like red light, hazard stop, relative angle etc as point wise metric

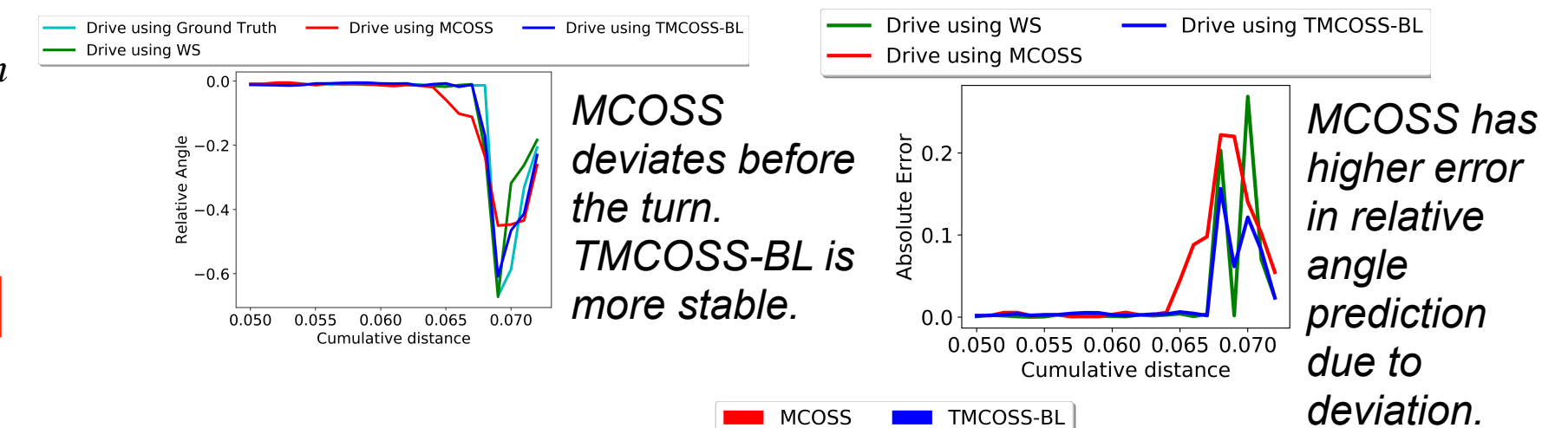
### TMCOSS-BL

Bucket specific Loss of relative angle and combined loss of other affordances as point wise metric

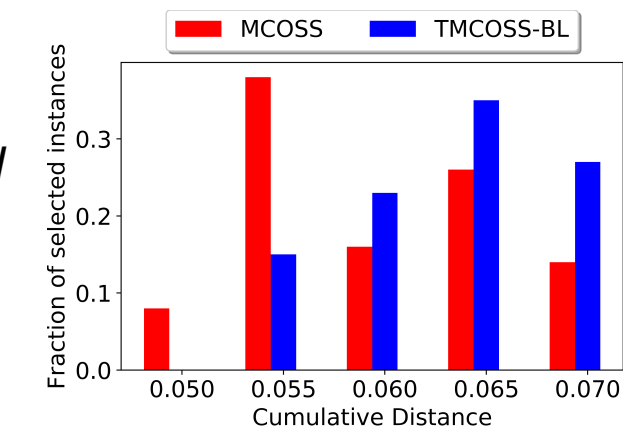
## Episode completion using CARLA simulator(100:7 compression)

Method	Train One-turn	Test One-Turn
Whole Set	10/10	10/10
MCOSS[2]	5/10	4/10
TMCOSS-TL	<b>7/10</b>	<b>9/10</b>
TMCOSS-BL	<b>8/10</b>	<b>9/10</b>

## Analysis: Failed episode by MCOSS but completed by TMCOSS-BL



MCOSS selects more instances on straight road bucket. TMCOSS-BL selects informative frames in required buckets.



## Semantic segmentation(IoU)using DeepLabV3+ [4] on Cityscapes

Method	Road	Sidewalk	Person	Car
Whole Set	98.0	83.0	81.0	94.0
MCOSS[2]	96.0	75.0	74.0	90.0
TMCOSS	<b>98.0</b>	<b>82.0</b>	<b>79.0</b>	<b>93.0</b>

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