TALoS: Enhancing Semantic Scene Completion via Test-time Adaptation on the Line of Sight

NeurIPS 2024

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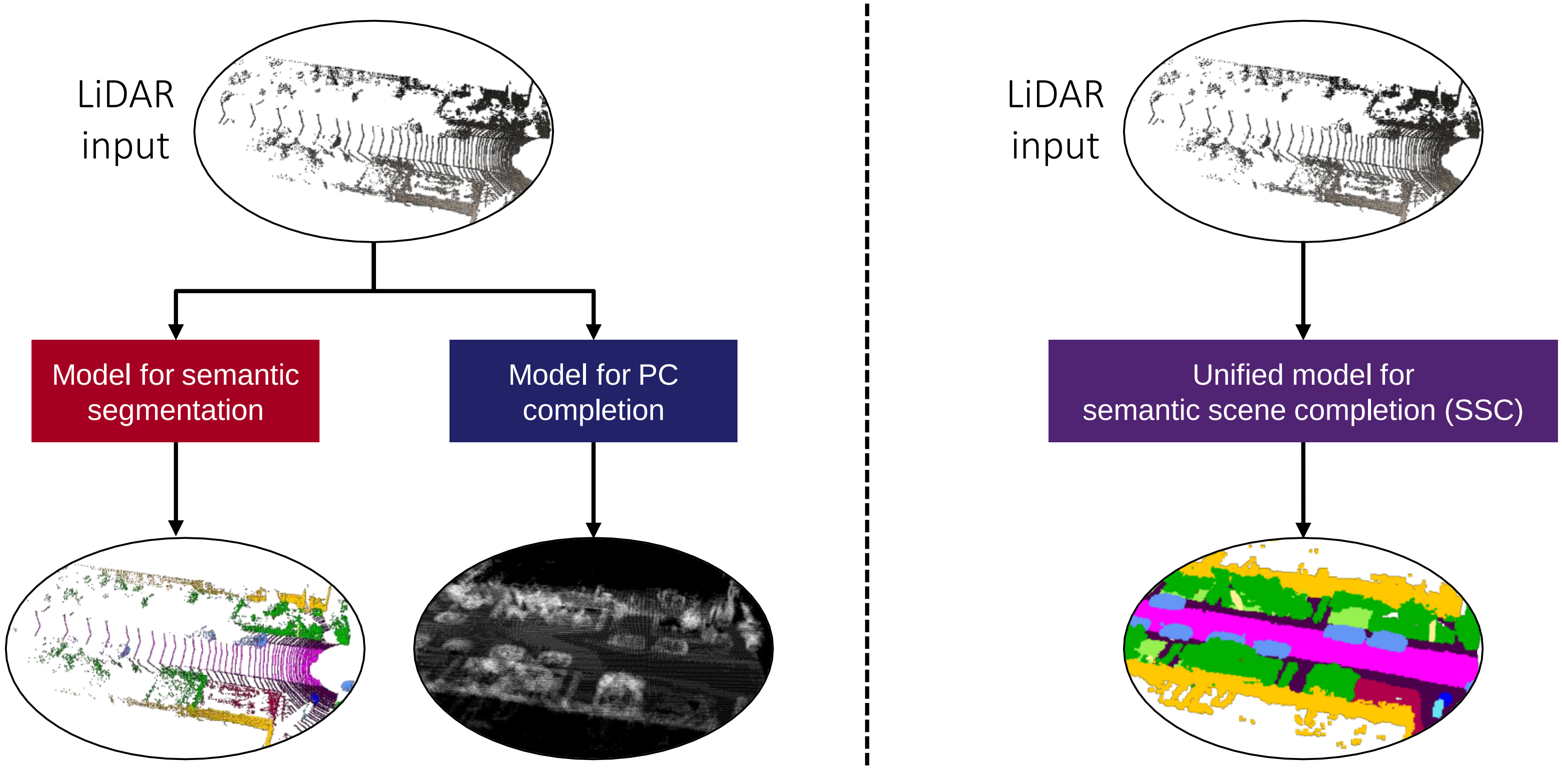
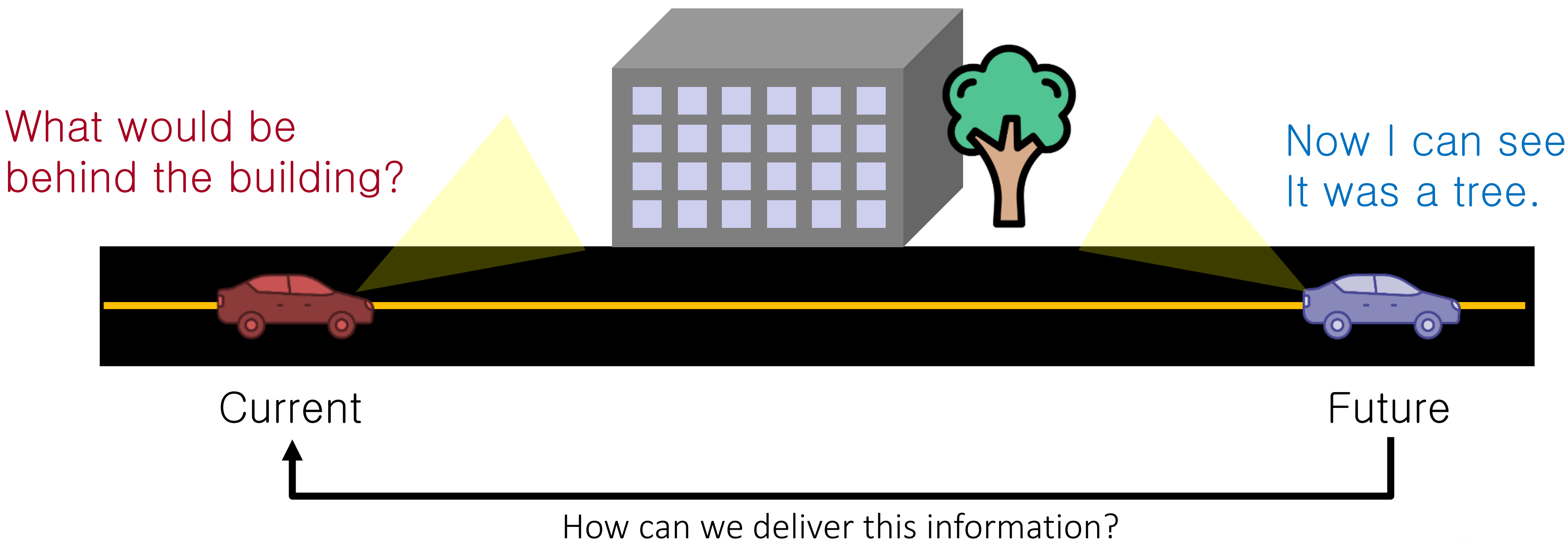
Introduction

- LiDAR Semantic Scene Completion (SSC)
  - Aim to solve semantic segmentation & point cloud completion task at once



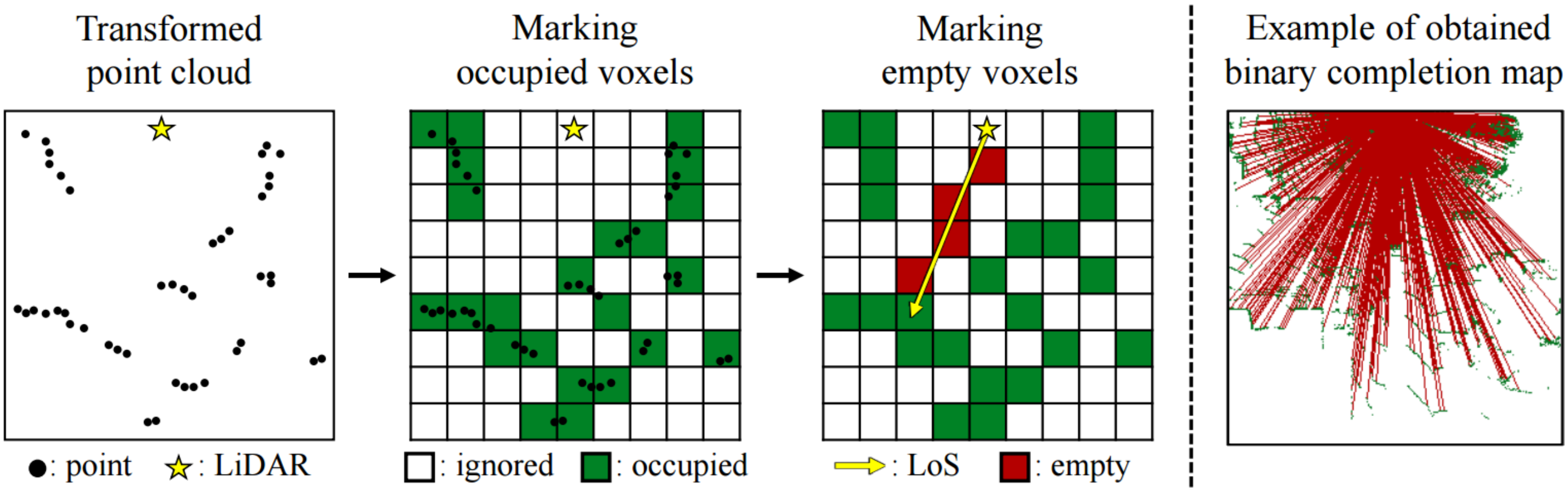
Motivation

- Observations from different moment for SSC prediction
  - Observation at one moment can be a clue for SSC prediction at the other moment.
  - We propose a test-time adaptation approach, **self-enhancing the SSC model** using this idea.



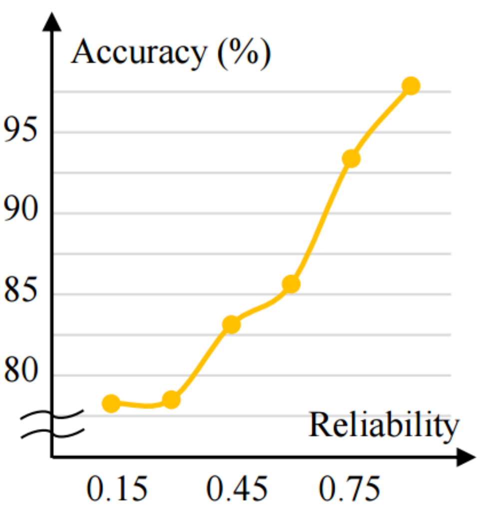
Methods

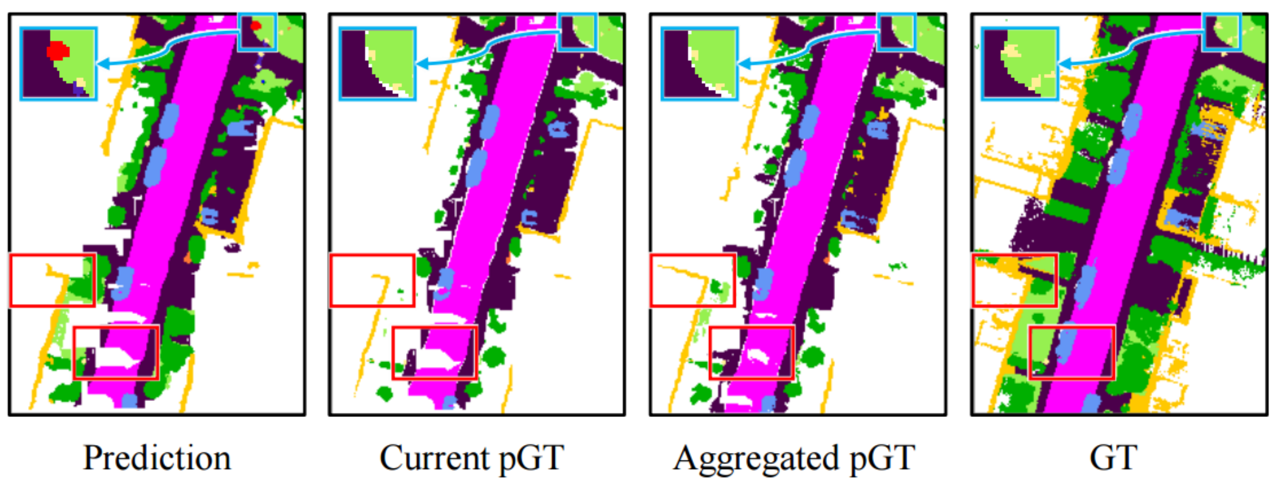
- Test-time Adaptation via Line of Sight (TALoS)
  - We apply a transformation to point cloud from another moment mark occupied in voxels.
  - We use the **Line of Sight to identify which voxels should not be occupied.**
  - Generated binary completion map serves as **supervision for enhancing completion**.



Methods

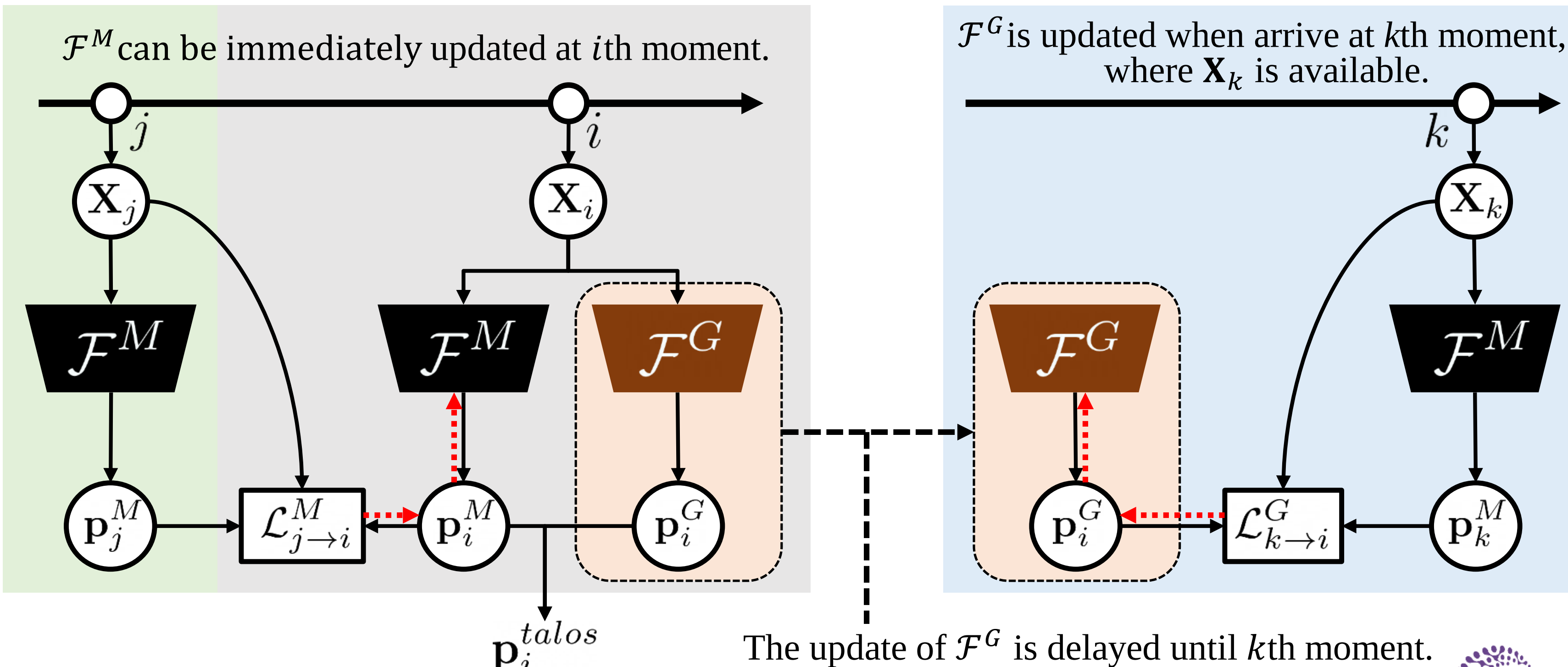
- Extension for semantic perception
  - We measure reliability of prediction and utilize only reliable points for pseudo-GT.
  - We obtain pseudo-GT from the current and another moment, then aggregate them.
  - Final pseudo-GT serves as **supervision for addressing perception of surroundings.**





Methods

- Dual optimization scheme for gradual adaptation
  - We propose dual optimization scheme to effectively adapt the model.
  - Our approach involves two models: $\mathcal{F}^M$ **for instant adaptation,** $\mathcal{F}^G$ **for gradual adaptation**.



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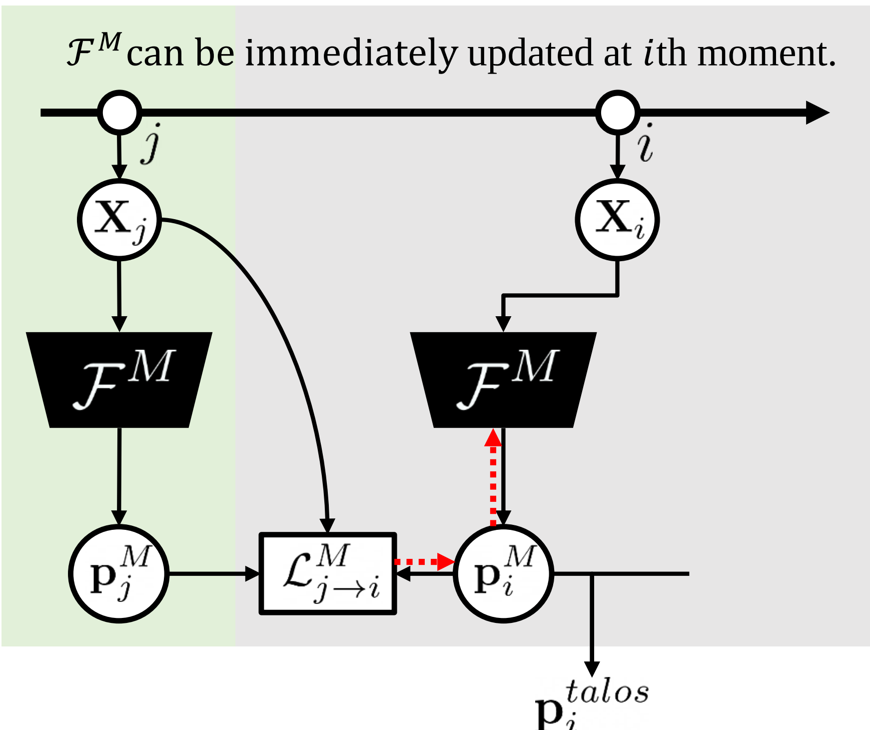
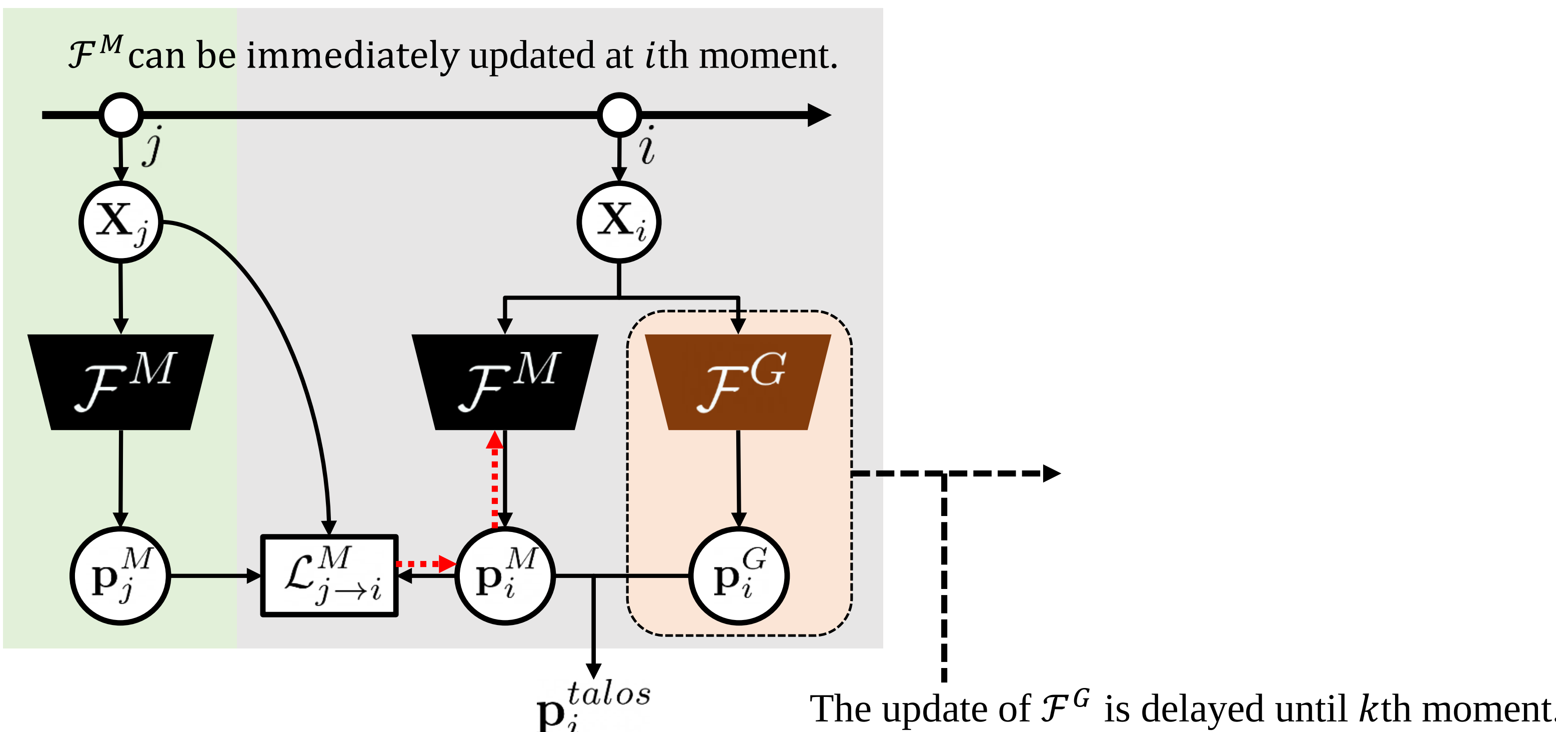
Methods

- Dual optimization scheme for gradual adaptation
  - We simply utilize current and previous moment for updating $\mathcal{F}^M$.
  - We initialize $\mathcal{F}^M$ every moment and discard it at the end of the moment.



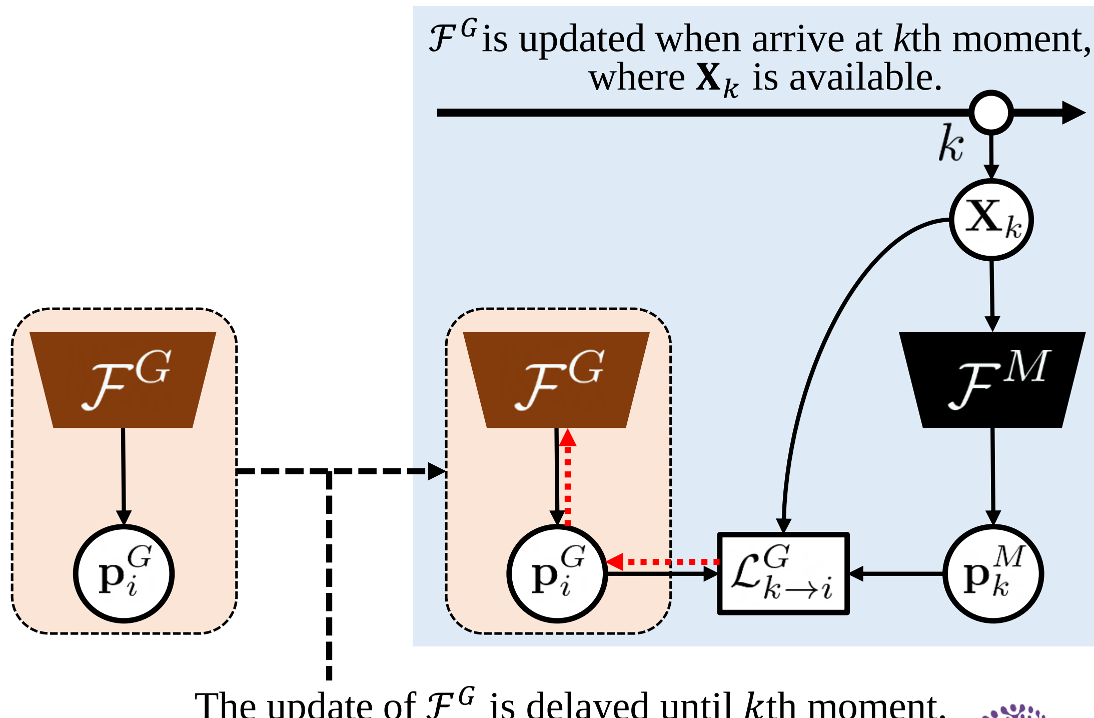
Methods

- Dual optimization scheme for gradual adaptation
  - The guidance from future observations can be more important and valuable than the past.
  - **We delay the update until future observations become available.**



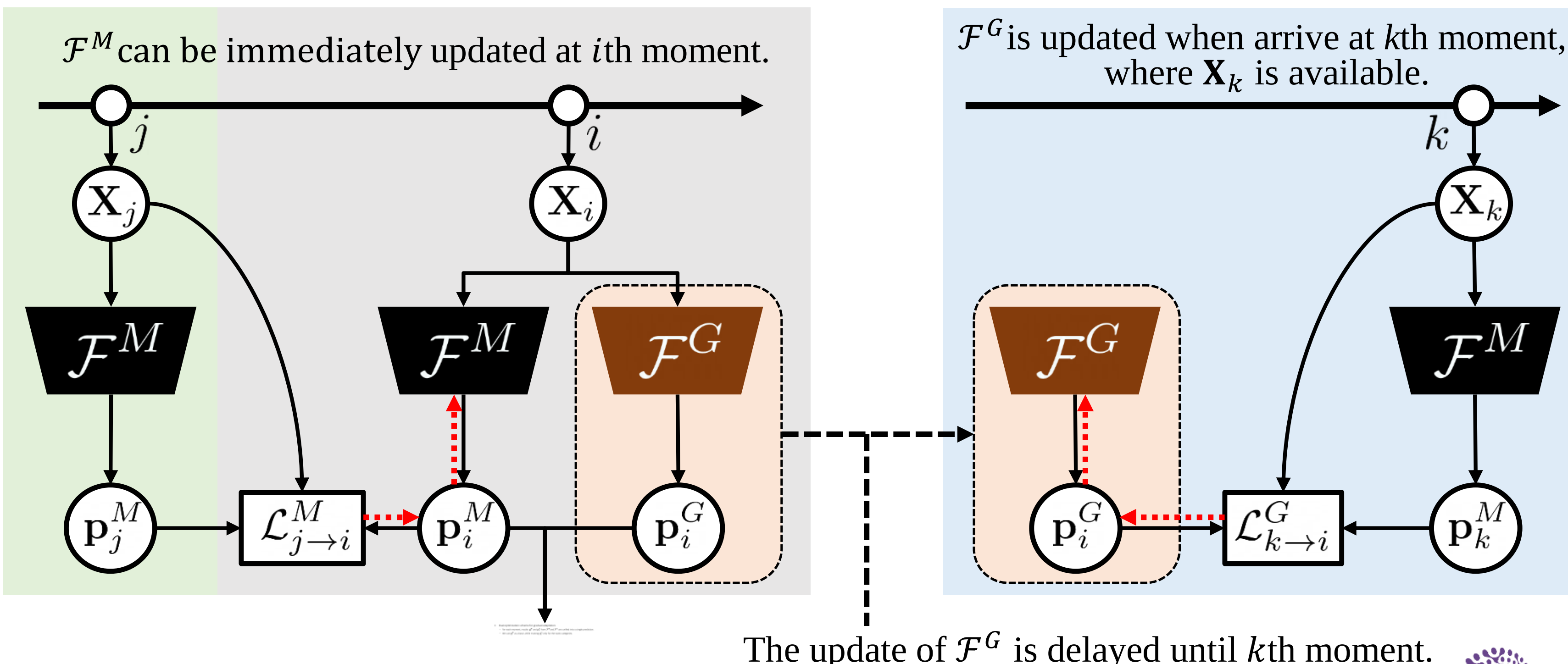
Methods

- Dual optimization scheme for gradual adaptation
  - Once $\mathcal{F}^G$ arrives at next moment (which was future at prediction), the update is performed.
  - We initialize $\mathcal{F}^G$ only at the first step and continuously utilize it for prediction.



Methods

- Dual optimization scheme for gradual adaptation
  - For each moment, results $\mathbf{p}_i^M$ and $\mathbf{p}_i^G$ from $\mathcal{F}^M$ and $\mathcal{F}^G$ are unified into a single prediction.
  - We use $\mathbf{p}_i^M$ as a base, while trusting $\mathbf{p}_i^G$ only for the static categories.



Experimental Results

- Quantitative Analysis

Methods	mIoU	cIoU	car	bicycle	motorcycle	truck	other-vehicle	person	bicyclist	motorcyclist	road	parking	sidewalk	other-ground	building	fence	vegetation	trunk	terrain	pole	traffic-sign
SSA-SC [6]	23.5	58.8	36.5	13.9	4.6	5.7	7.4	4.4	2.6	0.7	72.2	37.4	43.7	10.9	43.6	30.7	43.5	25.6	41.8	14.5	6.9
JS3C-Net [5]	23.8	56.6	33.3	14.4	8.8	7.2	12.7	8.0	5.1	0.4	64.7	34.9	39.9	14.1	39.4	30.4	43.1	19.6	40.5	18.9	15.9
S3CNet [16]	29.5	45.6	31.2	**41.5**	**45.0**	6.7	16.1	**45.9**	**35.8**	**16.0**	42.0	17.0	22.5	7.9	**52.2**	31.3	39.5	34.0	21.2	31.0	24.3
SCPNet [3]	36.7	56.1	**46.4**	33.2	34.9	13.8	29.1	28.2	24.7	1.8	68.5	**51.3**	49.8	**30.7**	38.8	44.7	46.4	**40.1**	48.7	40.4	**25.1**
TALoS	**37.9**	**60.2**	**46.4**	34.4	36.9	**14.0**	**30.0**	30.5	27.3	2.2	**73.0**	**51.3**	**53.6**	28.4	40.8	**45.1**	**50.6**	38.8	**51.0**	**40.7**	24.4

	Loss functions		Dual optimization scheme		Metrics	
	COMP	SEM	MOMENT	GRADUAL	mIoU	cIoU
Baseline					37.56	50.24
A	✓		✓		37.97	52.81
B		✓	✓		38.35	52.47
C	✓	✓	✓		38.38	52.95
D	✓	✓		✓	38.81	55.94
E (Ours)	✓	✓	✓	✓	**39.29**	**56.09**

COMP & SEM: use of loss function, MOMENT & GRADUAL: use of $\mathcal{F}^M$ and $\mathcal{F}^G$

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Experimental Results

- Qualitative Analysis