



# Domain Adaptive Imitation Learning from Visual Observation

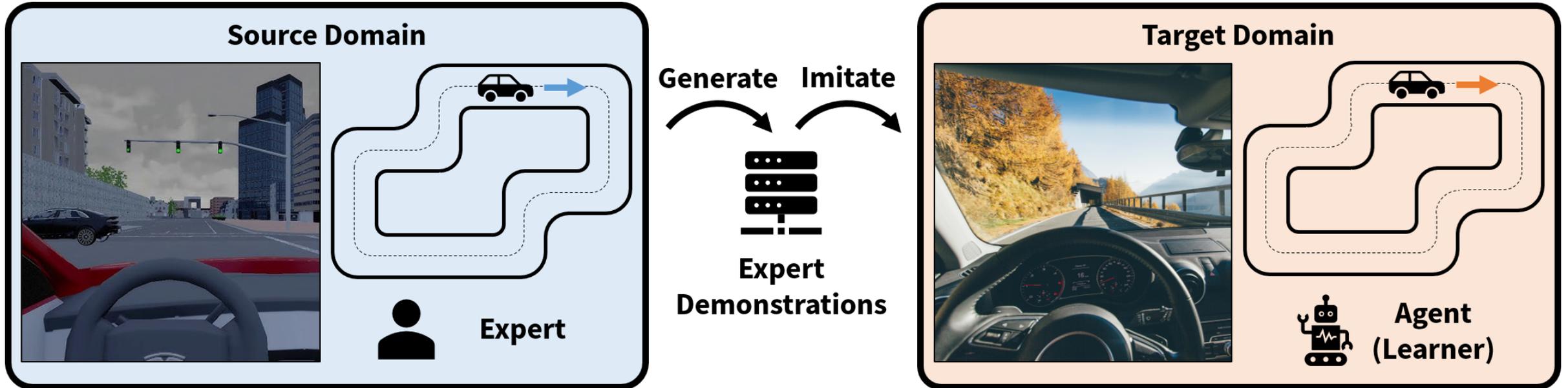
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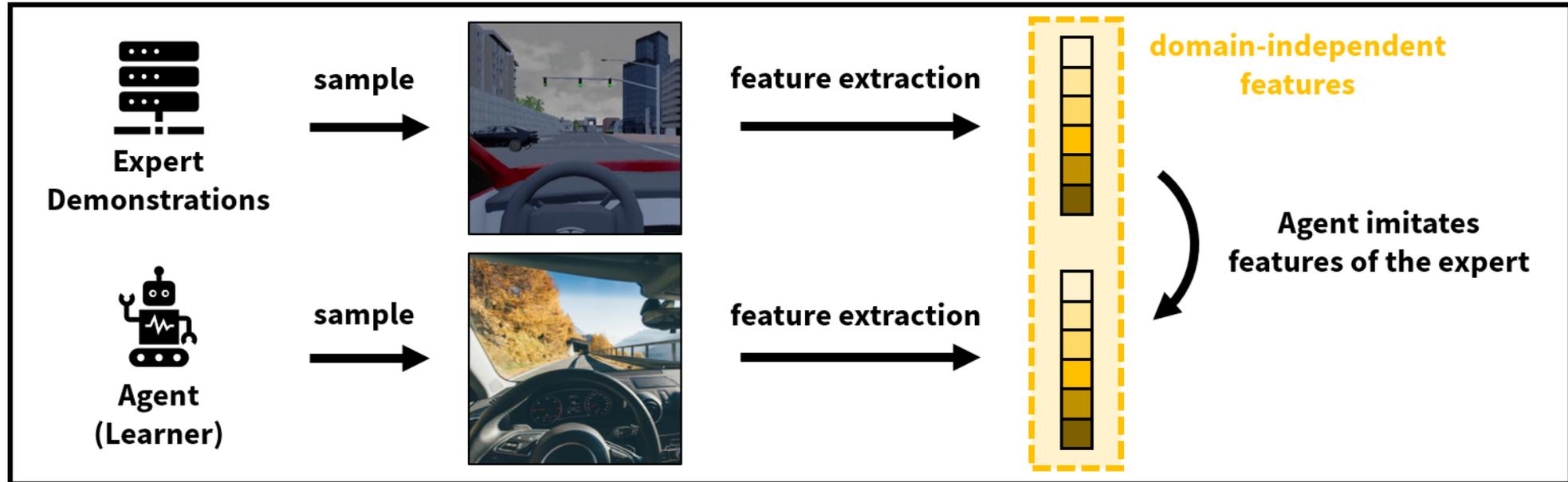
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# Imitation Learning (IL) with Domain Shift



- Learns behaviors by imitating expert demonstrations without access to true rewards
- Domain shift in IL: Expert domain (**source domain**)  $\neq$  Agent domain (**target domain**)
- We focus on the case where the **demonstrations are provided as visual observations**.

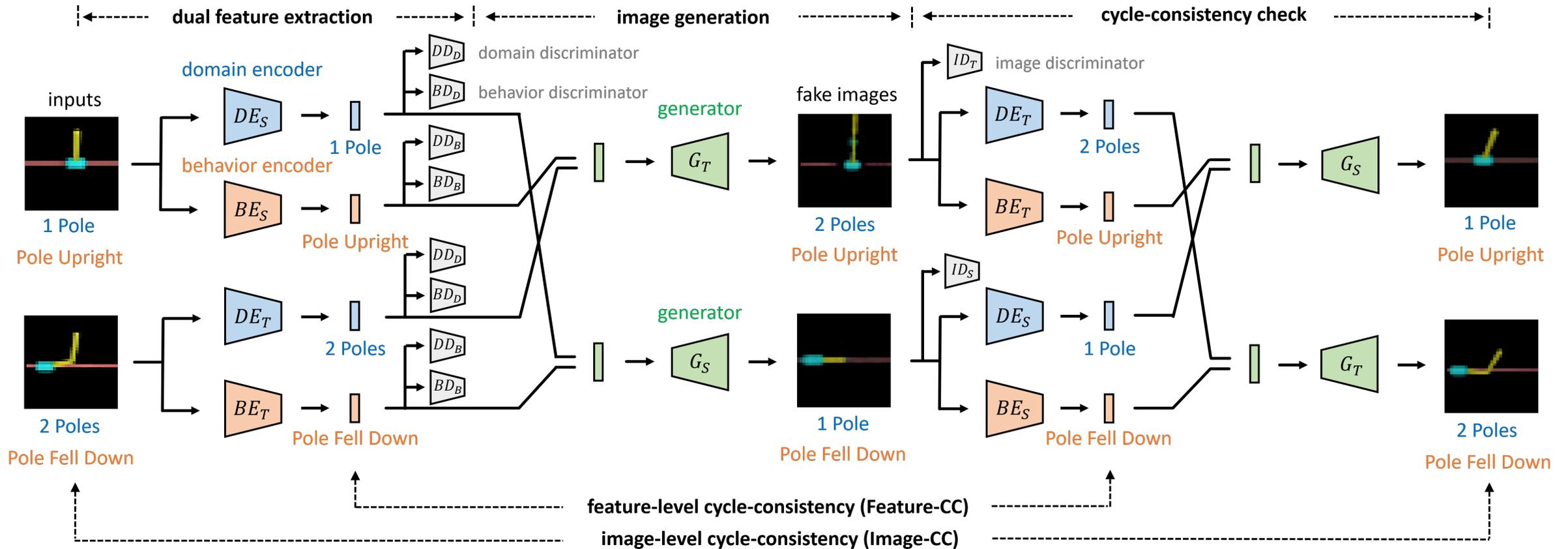
# A Problem in Imitation Learning with Domain Shift



- Due to domain shift, the learner cannot directly mimic the expert demonstration.
- We proposed *D3IL (Dual feature extraction and Dual cycle-consistency for Domain adaptive IL with visual observation)* for enhanced feature extraction and policy update.

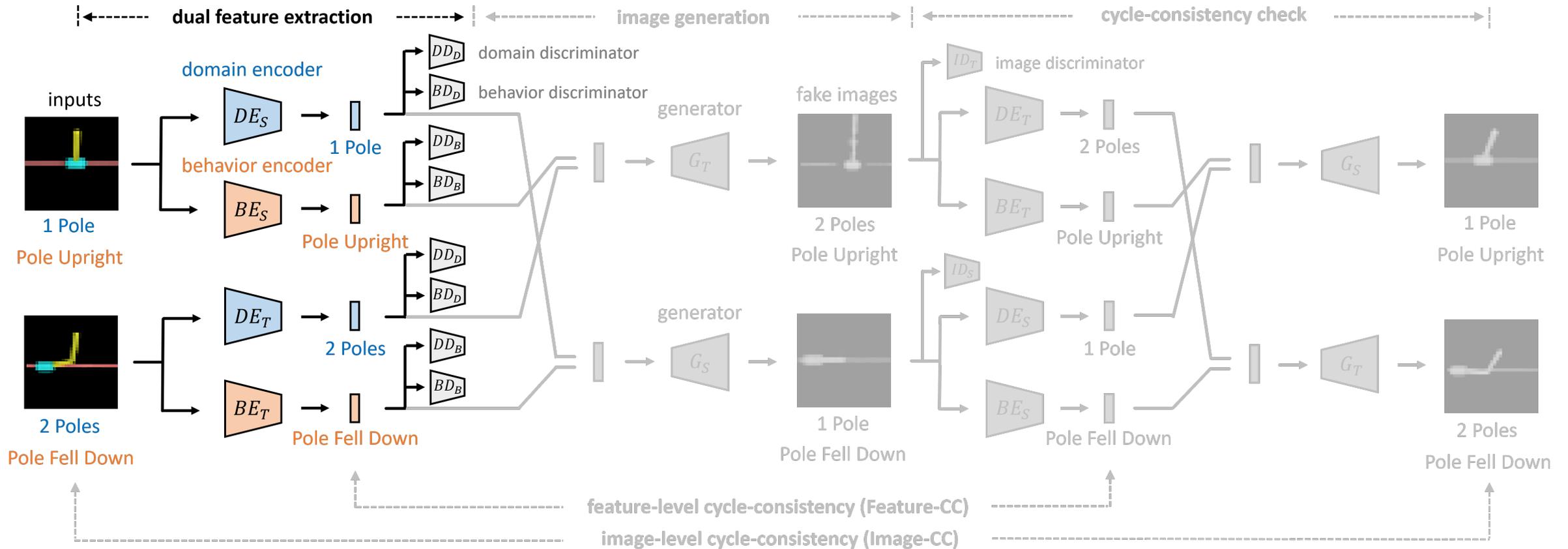
# Methodology

- Our feature extraction model is built based on the ideas of **dual feature extraction**, **image generation**, and **dual cycle consistency**.



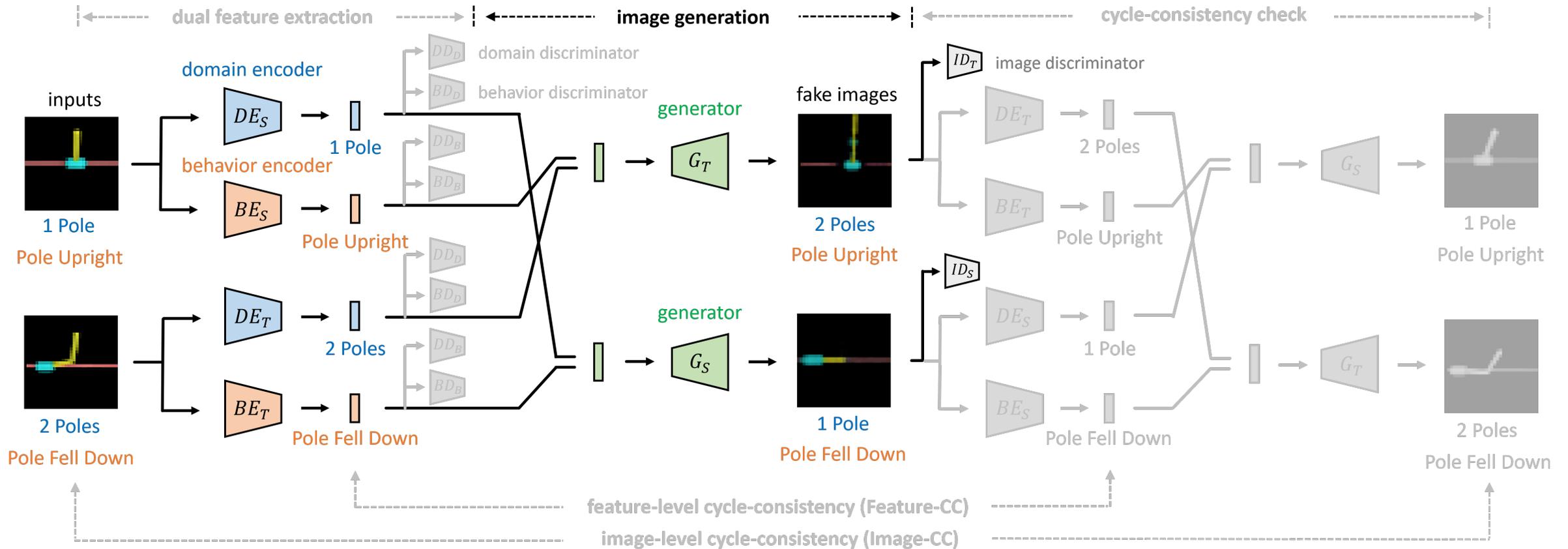
# Dual Feature Extraction

- The **domain feature** contains only domain information of the input.
- The **behavior feature** contains only task-relevant information of the input.



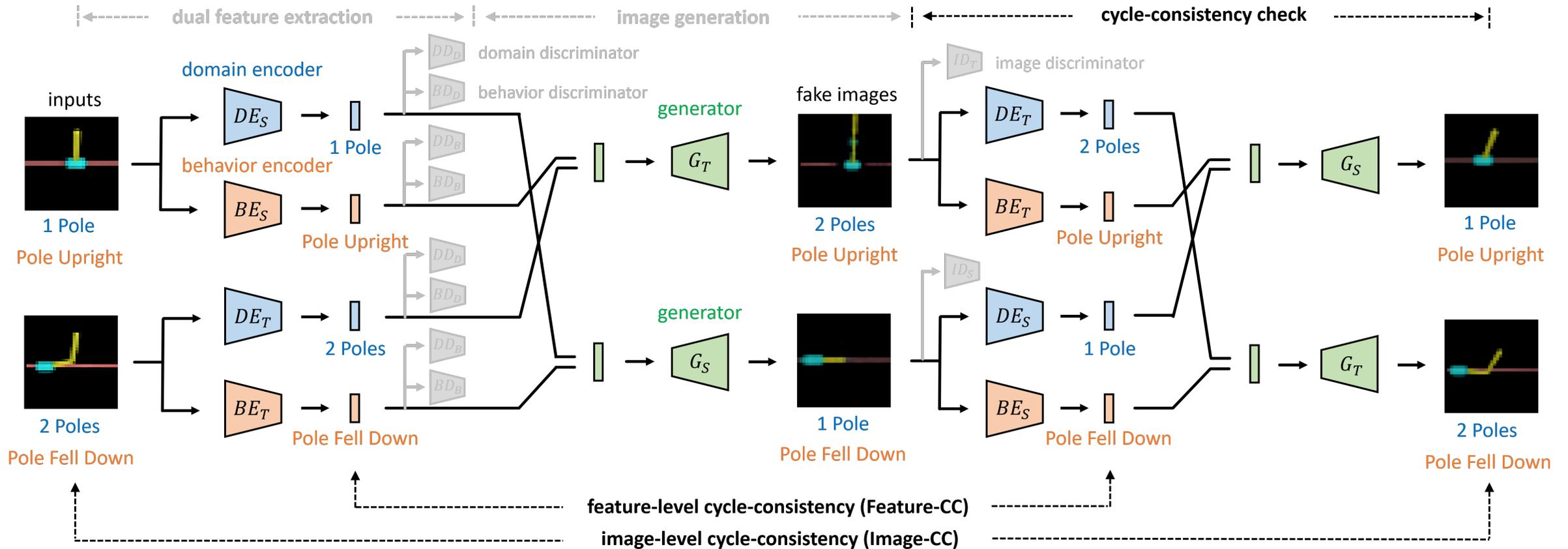
# Image Generation

- The generators produce images that contain domain and behavioral characteristics.



# Dual Cycle-Consistency

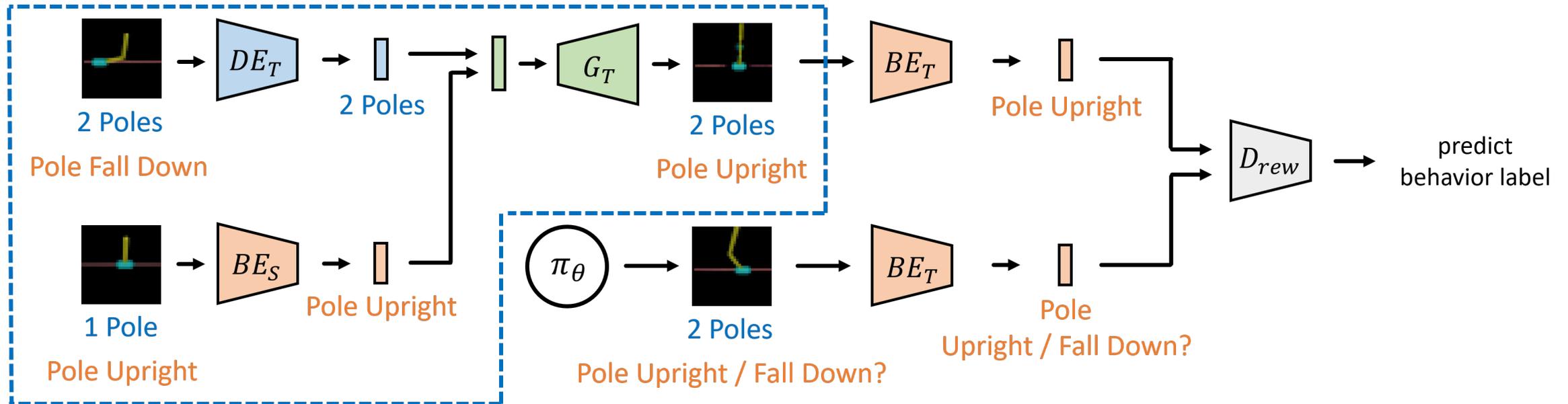
- Input **images** = **Images** after applying feature extraction and image generation twice
- **Features** via first-stage feature extraction = **Features** via second-stage feature extraction



# Reward Generation and Learner Policy Update

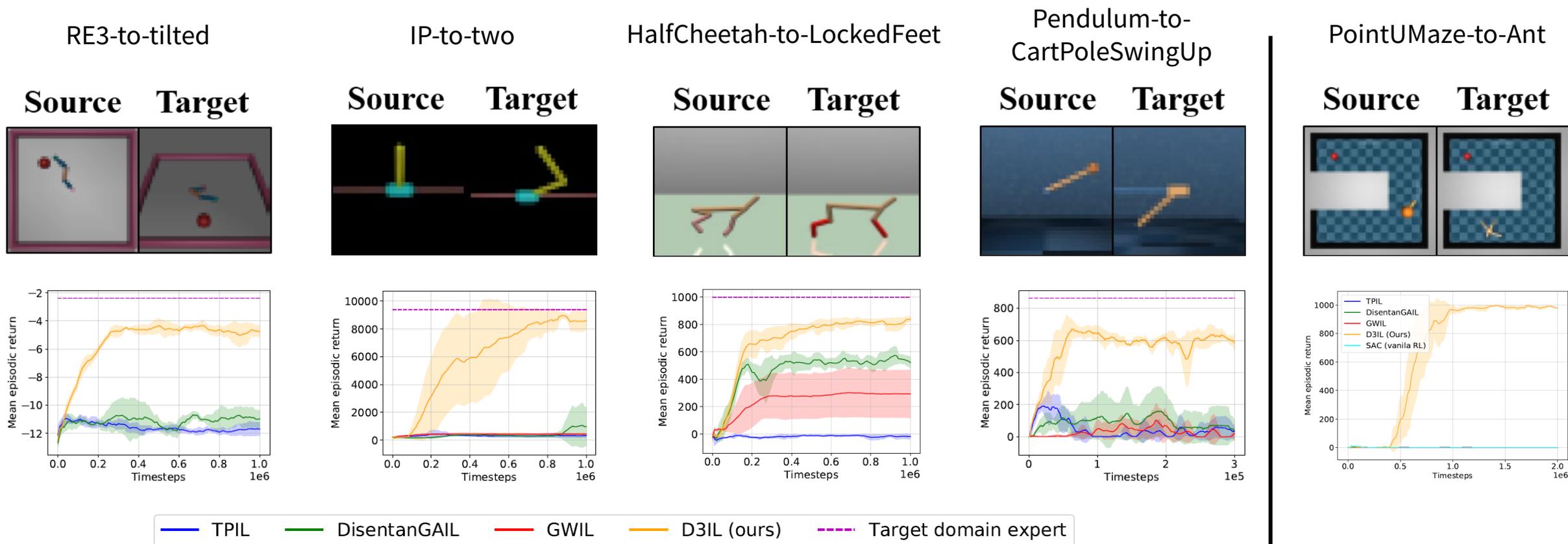
- Adversarial learning between reward-generating discriminator  $D_{rew}$  and policy  $\pi_\theta$
- The imitation reward for an observation  $o_t$  is defined by

$$\hat{r}(o_t) = \log D_{rew}(BE_T(o_t)) - \log(1 - D_{rew}(BE_T(o_t)))$$



# Experiments

- We evaluated D3IL on imitation learning tasks with **various types of domain shifts**.
- D3IL is also effective when directly obtaining a target domain expert is challenging.



# Thank You!

- If you have any questions, feel free to ask during the poster session.
- Poster Session 3 ([Wed 13 Dec 10:45 a.m. CST — 12:45 p.m. CST](#))
- Poster Location: [Great Hall & Hall B1+B2 #1406](#)
- E-mail: [sungho.choi@kaist.ac.kr](mailto:sungho.choi@kaist.ac.kr)